Making Apps: An Approach to Recruiting Youth to Computer Science

JODY CLARKE-MIDURA and CHONGNING SUN, Department of Instructional Technology and Learning Sciences, Utah State University
KATARINA PANTIC, Teacher Education Department, Weber State University

In response to the need to broaden participation in computer science, we designed a summer camp to teach middle-school-aged youth to code apps with MIT App Inventor. For the past four summers, we have observed significant gains in youth's interest and self-efficacy in computer science, after attending our camps. The majority of these youth, however, were youth from our local community. To provide equal access across the state and secure more diversity, we were interested in examining the effect of the camp on a broader population of youth. Thus, we partnered with an outreach program to reach and test our camps on youth from low-income high-poverty areas in the Intermountain West. During the summer of 2019, we conducted two sets of camps: locally advertised app camps that attracted youth from our local community and a second set of camps as part of a larger outreach program for youth from low-income high-poverty areas. The camps for both populations followed the same design of personnel, camp activities, structure, and curriculum. However, the background of the participants was slightly different. Using survey data, we found that the local sample experienced significant gains in both self-efficacy and interest, while the outreach group only reported significant gains in self-efficacy after attending the camp. However, the qualitative data collected from the outreach participants indicated that they had a positive experience both with the camp and their mentors. In this article, we discuss the camp design and findings in relation to strategies for broadening participation in Computer Science education.

CCS Concepts: • **Social and professional topics → Informal education**;

Additional Key Words and Phrases: Middle school youth, near-peer mentor, high school youth, self-efficacy, interest, access, diversity

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Authors' addresses: J. Clarke-Midura and C. Sun, Department of Instructional Technology and Learning Sciences, Utah State University, 2830 Old Main Hill, Logan, UT 84322, USA; emails: jody.clarke@usu.edu, vincent.sun@aggiemail.usu.edu; K. Pantic, Teacher Education Department, Weber State University, 1351 Edvalson St., Dept 1304, Room# 335, Ogden, UT 84408-1304, USA; email: katarinapantic@weber.edu.

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1 INTRODUCTION

In recent years, there has been a surge of research that aimed to broaden participation in Computer Science (CS) education. Some studies examine the influence of different media for delivering programming, such as coding toys for children, e.g., [17] or online learning platforms, such as Scratch, e.g., [32, 75, 84] or MIT App Inventor, e.g., [21, 39, 69, 76]. Other studies look at the influence of social support, such as mentors, e.g., [16, 19, 28, 52] and or parents, e.g., [18]. Most of the above-mentioned interventions and pedagogies have been found to have a positive effect on participation of youth in CS education. Some recent reports even pointed out that CS enrollment has increased in recent years, e.g., [23, 70]. However, in the United States, CS education is still dominated by white male participants (see [22, 71]) and the need to broaden participation still exists [72]. In response to this call for extending CS opportunities to underrepresented youth, we designed a summer camp experience to teach middle-school youth to code apps by using MIT App Inventor. The overarching goal of our project was to identify strategies that broaden participation, for girls in particular. For the past four summers, we observed significant gains in youth's self-efficacy and interest, after attending our App camps, e.g., [19, 21]. While we achieved our goals to reach more girls, our attempts to recruit a demographically diverse sample was not as successful. Therefore, we partnered with an outreach program that worked with youth across the state to reach a more demographically diverse sample. According to Warner, Fletcher, and Garbrecht [107], providing access to youth from low-income schools and securing participation of underrepresented subgroups are two of the four major components of achieving equity in CS education, in addition to securing the quality of instruction and CS qualified teachers. The purpose of this article, therefore, is to explore the effectiveness of our camp on two different samples in terms of their affect towards CS. Specifically, we asked: Does participating in App camp affect campers' self-efficacy in programming? Does participating in App camp affect campers' interest in programming? Do we see a difference in self-efficacy and interest in programming between the two samples? To further understand the outreach campers' experience, we added two additional research questions: How do the outreach campers feel about the camp? How do the outreach campers feel about their mentors?

2 LITERATURE REVIEW

2.1 The Role of Self-efficacy and Interest in our Choice of Activity

Factors that promote and/or increase self-efficacy are central to our work. Self-efficacy refers to the individual's belief in his/her abilities to perform a task and it plays a critical role in human agency [8]. As Bandura [10] posited, self-efficacy is a major determinant of whether an individual chooses to partake in or avoid an activity, how much effort that person invests in the activity, and how long s/he persists in the face of difficulties. In accordance with this theorization on self-efficacy and choice of activities, literature on underrepresentation in CS has found empirical evidence showing that low self-efficacy is an important factor that precludes certain underrepresented groups from pursuing CS, e.g., [4, 33, 87, 96, 109].

In addition to its role in determining people's choice of activities, self-efficacy plays a critical role in interest development. According to social cognitive career theory [57], a theory built upon social cognitive theory [9] to explain academic and career interest development, self-efficacy is a precursor to interest. In other words, people will form an enduring interest in an activity in which they feel efficacious or confident. A plethora of research has lent empirical support to attest to the relationship between self-efficacy and interest. As an example, one study [58] investigating factors that predict college students' interest and career goals in the computing disciplines showed that self-efficacy is predictive of interest. This indicates that high self-efficacy had the potential to increase positive interest in majoring in computing disciplines. In another study, Luse, Rursch, and

Jacobson [63] examined factors that affected high school students' choice of information technology as a major. They also found a significant positive relationship between self-efficacy and interest.

It is also worth mentioning though that despite their positive relationship, researchers found a temporal lag between recently acquired self-efficacy and resultant interest [9, 57]. In other words, newly acquired self-efficacy may not lead to an immediate change in interest, and it may take multiple or extended experiences of increased self-efficacy to affect a change in interest.

2.2 Self-efficacy in CS Education

There is a considerable number of studies on self-efficacy in the CS education literature, and a majority of them were conducted in higher education, e.g., [54, 64, 78, 81]. A notable group of CS self-efficacy research in higher education is characterized by the interest of investigating the relationship between self-efficacy and students' pathway to CS, e.g., [25, 26, 60, 85]. For example, one study [85] found that in addition to social support, self-efficacy was positively associated with undergraduate students' orientation toward computer and information science careers. That is, higher self-efficacy predicted stronger orientation. In another study, where a survey was administered to students in an introductory CS course, measuring their intentions to further pursue computer science, Dempsey and colleagues [25] found that CS self-efficacy and identity were significantly correlated with intentions to pursue CS in the future.

In addition to the pathway studies mentioned above, there is a large body of research that investigated self-efficacy in CS in the context of broadening participation, e.g., [2, 12, 14, 15, 56, 96]. For example, Blaney and Stout [15] surveyed students in a CS1 class and found that females in general had lower computing self-efficacy and sense of belonging than males. In addition, first generation college females reported significantly lower self-efficacy and belonging compared to their peers (i.e., males and continuing generation females). In another study, Lehman and colleagues [56] used a national sample of first-year college students to understand more about the characteristics and backgrounds of women who planned to major in CS including ethnic and racial backgrounds, academic achievement, and affective attitudes. They found that females had significantly lower computing self-efficacy compared to males. This self-efficacy inequity between female and male college students is consistent across numerous studies, e.g., [11–14, 33, 104]. According to a review of the literature by Singh et al. [96], research suggests that female college students have lower CS self-efficacy than their male peers.

Another strand of self-efficacy studies in CS education focuses on K-12 students, particularly from the perspective of recruitment. A number of studies found that self-efficacy was an important contributing factor that shaped K-12 students' CS-related career aspirations, e.g., [34, 40, 41]. For example, Sáinz and Eccles [92] found that self-concept of computer ability (defined as self-perceptions of one's ability with computers, such as how good one is at computers) predicted Spanish high school students' intentions to pursue ICT-related studies in the future. Additionally, Friend [34] compared the interest and confidence in computing of middle school girls and found that girls who were open to a computing career had higher interest and confidence than those who did not want a computing career. In addition, in a report prepared for an NSF project on women/girls' lack of participation in CS, Gürer and Camp [41] concluded that loss of self-efficacy affected women/girls at all levels of the CS pipeline, and it was a major cause for K-12 girls not entering CS and for college women leaving CS.

Given the important role self-efficacy plays in recruiting students to CS, a plethora of CS education research in K-12 sector was designed to increase youths' self-efficacy, and the majority of these studies were conducted in out-of-school settings, e.g., [1, 3, 27, 50, 53, 74, 80, 86, 90, 102, 103]. In a recent study published in this journal [see 21], the authors conducted a review on computing camps for youth. They found that the effects of these camps on students' self-efficacy were inconsistent. While several studies reported significant post-camp gain in self-efficacy, e.g., [19, 90, 98, 103], one study did not observe a significant change in self-efficacy [102]. In addition, some studies observed mixed results [50, 86]. Furthermore, as for those studies that observed significant self-efficacy gains, there is a vast difference in the magnitudes of change. For example, Gannod et al. [35] ran a summer residential camp where high school girls learned to code mobile apps. They only recorded a small change in post self-efficacy (i.e., Cohen's d = 0.20). Another study [90] using the same strategy (i.e., coding mobile apps) and working with the same population (i.e., high school girls), reported a very large change in self-efficacy, Cohen's d = 1.71. This review shows that our understanding of self-efficacy within informal CS environments is still far from complete and more research is needed on what strategies can build youths' self-efficacy.

2.3 Interest in CS Education

Similar to findings around self-efficacy, the gender difference in interest in CS education has also persisted for decades [94] and is well-documented in the CS education literature, e.g., [4, 29, 105, 106]. Although girls' report a similar level of interest in CS as boys at early ages, girls tend to lose interest as they grow older [67, 68]. Research suggests that the lack of interest among adolescent girls and young adult women is directly linked to females' lack of participation in CS education [63, 94]. Therefore, numerous initiatives have been designed to increase interest in CS, particularly for females [15, 37].

Due to evidence that shows academic and career interest disparity begins to emerge as early as in secondary school [6, 91], many initiatives (including ours) focus on middle- and high-school-aged youth [27, 73, 86]. Despite numerous efforts to increase youth's interest in CS, the results are still mixed and often do not show significant change, e.g., [90, 98, 108]. For example, two different studies [86, 102] used the same programming platform (i.e., App Inventor) with similar course delivery approach (i.e., self-paced video tutorials), and both focused on high-school-aged youth. Urness and Manley [102] did not observe any significant change in interest after the camp. However, Roy [86] administered a survey and conducted analysis where they examined change in interest by each individual item (as opposed to a latent construct). The authors found that some items showed increase, and some showed no change or even decrease.

According to Graves and DeLyser [38], these inconsistent findings in interest gains can be attributed to how interest was measured. In other words, measures of interest often do not differentiate students' situational interest and intrinsic or individual interest—two distinctive constructs reflecting two different developmental stages of interest. According to Hidi and Renninger [46], in their model of interest development, interest progresses in four sequential and distinct stages: triggered situational interest, maintained situational interest, emerging individual interest, and well-developed individual interest. Situational interest refers to the psychological state and affective reaction to an external (e.g., an object or an environmental condition) stimulus in the moment, while individual interest is an enduring predisposition to seek repetitive engagement in an activity over time. In addition, situational interest is the precursor to individual interest, and it takes time for the former to turn into a well-developed individual interest. This developmental view of interest is different from that in the vocation and career literature such as Holland's vocational choice and interest types [47, 48], where interest is conceptualized as a well-developed personal trait. According to Hidi and Renninger [46], the conceptualization of interest as a stable construct can cause problems and the little to no interest change observed in some vocational interest studies is likely due to this view of interest. Therefore, Renninger and Hidi [82] argued that when measuring interest, researchers should be clear about how to conceptualize interest; otherwise, the empirical findings may not be helpful in informing the decisions on how to generate interest.

In the present study, we adopted Hidi and Renniger's four stage model of interest [46]. In doing so, we argue that while we may not be able to change youths' individual interest, we are striving to trigger their situational interest in programming, which is important for broadening participation. However, to the best of our knowledge, there is only a handful of studies on situational interest in the CS education and recruitment literature, e.g., [55, 61, 95]. Lakanen et al. [55] and Scaico et al. [95], for example, used a qualitative approach to investigating the trajectories of interest development (i.e., from situational interest to individual interest) among high school graduates who attended a programming camp before, and college freshmen enrolled in a CS0 course, respectively. Lakanen and colleagues [55] found that while it did not affect many students, attending the programming camp was beneficial to those who already had a maintained situational interest. Namely, attending the camp strengthened their confidence in studying CS. As to the Scaico et al. [95] study, they found six trajectories of how interest developed among ten students, representing three patterns: evolving to a more developed state, regressing to a lesser developed one, and remaining at the same state over a long period of time. They also found that one individual could demonstrate multiple trajectories over time. In addition, the study also identified a few factors that could trigger situational interest, including learning of peers' successful coding experience, task novelty, and completing the first code.

3 CONTEXT

Our camp focused on how to program apps using MIT App Inventor, a block programming language used to develop mobile applications running Android OS [36]. We selected App Inventor, because it has a low entry threshold for novice programmers.

3.1 Near-peer Mentoring Model

As mentioned above, our camps were specifically designed around strategies to broaden participation in CS. We developed a near-peer mentoring model where we trained high school youth with little or no CS background to program in App Inventor and to mentor their middle school peers. The high school mentors then helped us run our camps.

3.2 Camp Curriculum

The curriculum for this camp was delivered via Canvas, a learning management system. The curriculum is designed around 11 apps, with additional apps for advanced students. In the 11-app sequence, the content starts out easy by building a simple app that has a text to speech feature, to more complex apps that involve databases and conditionals. The instructions in the instructional material start out highly scaffolded, but once a concept is introduced, the step-by-step instructions are no longer provided for that concept. In addition, due to research that shows increasing the meaningfulness of and personal involvement in a task helps trigger and maintain interest [43, 46], we offered campers (and mentors) with the choice of personalizing their apps—a strategy used with an intent to increase task relatedness [43, 46, 89]. Specifically, campers were encouraged to personalize their apps in various ways from adding their own images to adding on features. In addition to building the basic apps, campers were engaged in debugging activities with their peers. For a list of all the apps and programming concepts covered in the camp, as well as a more detailed description of the curriculum, see Clarke-Midura et al. [21].

3.3 Mentor Training

During the summer of 2019, we ran two mentor training sessions for high school students who helped us mentor middle school youth in our local and outreach camps, respectively. The mentor training was designed to train high school youth how to code and be a mentor. In other words, they learned how to program the 11 apps aforementioned, how to debug, and how to approach youth while mentoring them. Some of the mentoring activities included asking questions, providing constructive feedback and so on. Mentor training lasted for five days (a total of 25 hours) and it was identical for the two sets of mentors.

All the mentors were supported by lead mentors during their training. Lead mentors were trained and worked as mentors in our 2018 camps. They were also high school students who modeled mentoring behavior for the trainees and offered programming help. The same lead mentors served as their supervisors in both the local and outreach camps.

3.4 Strategies Used to Promote Self-efficacy

As a precursor to interest [57], self-efficacy is central to our camp design. When designing our camp, we incorporated several strategies in line with Bandura's theorization [8–10] to promote self-efficacy:

3.4.1 Maintaining Levels of Task Difficulty. First, we designed our curriculum so that it proceeds in difficulty. As Bandura [8–10] posited, a task that is too easy does not contribute to raising self-efficacy; the same goes for a task that is too difficult. Failure to complete an exceedingly difficult task does not reflect an individual's ability, but it does discourage participation. Therefore, maintaining the difficulty of our curriculum at a manageable level has the advantage of keeping the participants engaged, while at the same time, it boosts their efficacious beliefs when they master the challenging tasks.

To lower the difficulty of our curriculum, we built scaffolds into our instructional materials, such as visuals, and worked examples, so that when the participants start, they do not feel overwhelmed. The scaffolds, however, fade as the instruction advances with a goal of challenging the participants to think through the problems.

3.4.2 Providing Encouragement. Encouragement is also effective in increasing self-efficacy [8–10]. During our camps, we trained our mentors to regularly provide positive feedback to the campers. For example, we asked the mentors to give verbal compliments that praise campers' achievement and effort. We also asked the mentors to leave motivational messages to the campers each day throughout the camp.

3.4.3 Providing Credible Models. People can also adjust their self-efficacy by observing others (i.e., models) [8–10]. A model's effectiveness in changing the observer's self-efficacy depends upon the perceived similarity between the model and the observer. A model with comparable ability can increase the observer's self-efficacy. Due to the importance of similarity in building self-efficacy, we selected near-peers (who are similar in age and expertise to the campers) to be mentors. In doing so, we provided the participants with models of people who can do computer science, so they could promote campers' confidence in CS. In previous studies, we found that campers who perceived their mentors as similar (in age and expertise) and encouraging were more likely to experience an increase in self-efficacy, e.g., [19, 20].

In addition to the near-peer mentors, we also designed and showed three one-minute-long videos featuring recent college graduates from rural areas of the Intermountain West. These graduates shared how they became interested in CS and what they liked about their CS-related job. One reason for selecting these models was to increase the perceived similarity between the models and the campers, to boost their confidence in pursuing CS. Second, we hoped that campers would relate to models with similar experiences to theirs, and the models' experiences would resonate with their self-concepts by creating a sense of belonging for the campers. In turn, such sense of belonging would facilitate the emergence of a positive inclination towards CS.

3.5 Local App Camps

After training our mentors, we ran four camps for middle-school-aged youth in our local community (see Section 3.2 for a description of the camp curriculum). The camps were five days long, 3 hours a day (15 hours total). The ratio of mentors to campers was 1:5 or 1:6. The cost of the camp was $40, with an early bird option of $35. Scholarships were available to anyone who requested one.

3.6 Outreach App Camps

In addition to camps described in Section 3.4, we ran two camps as part of a larger outreach program. The outreach program was designed to improve students' high school graduation and postsecondary enrollment rates, while at the same time raising students' awareness of postsecondary education and career options.

The outreach app camps used the same curriculum and resources as the local app camps, but they were filled with middle school youth from nine schools located in low-income high-poverty areas in the Intermountain West. They were also five days long and lasted for 3 hours per day. There was no cost for this camp. The youth were recruited by the outreach organization in their schools. These campers were also supported by mentors, and the ratio of mentors and campers was also 1:5 or 1:6.

4 METHODS

4.1 Participant Recruitment

4.1.1 Mentors. Mentors for the two camps were recruited together, following the same procedures. First, applicants had to complete an online application form. Next, they went through a phone interview process, where they were asked about their programing and mentoring experience, why they wanted to mentor and how they would approach different mentoring situations. Based on their availability, they were assigned to either one of the two camps. Within the camp, they were assigned to a group of five to six campers. All the mentors were local high school students.

Of note, we decided not to match mentors and mentees by their backgrounds, such as gender and ethnicity/race for two reasons. First, research shows inconsistent findings in regard to the effects of gender match on mentees' affective attitudes [7, 49, 62, 65]. Second, although there is research showing ethnicity/race match benefited students from non-dominant communities in terms of learning outcomes and their relationships with mentors [83, 97], there is no evidence, to our knowledge, suggesting that ethnicity/race match affects mentees' self-efficacy and interest.

4.1.2 Campers. We used two groups of participants in the present study. The majority of youth in the local app camps came from local schools, while the youth in the outreach camps were recruited from nine schools across the state. Of note, these nine schools were serving a high number of low-income students, where at least fifty percent of the student body were eligible for free or reduced lunch. All our camps had only one inclusion criteria, which was gender proportion, as the main goal of this study was to encourage girls' participation.

The two groups were recruited using different strategies, thus resulting in two samples representative of two different populations participating in out-of-school CS experiences. To recruit for our local app camps, we used fliers, social media, local publications, and school email systems. By contrast, the outreach camp participants were recruited by their school's teachers and counselors to participate in the outreach program.

Table 1. Demographic Information of the Two Samples

	Local App Camp	Outreach App Camp
Ethnicity		
LatinX	6%	25%
Race		
Asian	10%	7%
Native American/Pacific Islander	1%	2%
Black/African American	1%	0
White	77%	84%
Multi-Racial	5%	5%
Other	6%	2%
Socio-economic status		
Free/Reduced Lunch	19%	57%

4.2 Participants

In this section, we provide the demographic information of mentors and campers of the two camps, as well as the information on campers' parents'/guardians' occupations and the final samples used for analyses. All participants came from a rural area in the Intermountain West of the United States.

4.2.1 Mentors. Fifteen mentors participated in the local app camp (Female = 11, Male = 4; average age = 15). Racial makeup included 86% White (n = 13), 7% Multi-racial (n =1), and 7% Other (n =1). None reported being on free or reduced lunch.

Nine mentors participated in the outreach camp (Female = 5, Male = 4; average age = 15). Racial makeup included 33% Asian (n = 3) and 67% White (n = 6). Thirty-three percent (n = 3) reported being on free or reduced lunch.

4.2.2 Local App Camp Participants. We recruited 100 campers to attend the local app camps. Two girls were not included in any data collection due to lack of parental consent. Thus, the app camp sample consisted of 98 participants (Female = 58, Male = 40; average age = 12). Six percent self-identified as LatinX. Racial makeup included 10.2% Asian (n = 10), 1.0% Black/African American (n = 1), 1.0% Native American/Pacific Islander (n = 1), 76.5% White (n = 75), 5.1% Multi-racial (n = 5), and 6.1% Other (n = 6). Nineteen percent of the campers (n = 19) self-reported being on free or reduced lunch.

After preliminary analysis, we dropped 19 participants from the analysis due to the fact they had attended our 2018 camps (n = 11) or they stopped attending after the first day (n = 8). Therefore, our final number of participants used in this analysis was 87.

4.2.3 Outreach App Camp Participants. Forty-five campers attended the outreach camp (Female = 20, Male = 25; average age = 13). One male was excluded from the analysis due to lack of parental consent. Twenty-five percent self-identified as LatinX. Racial makeup included 6.8% Asian (n = 3), 2.3% Native American/Pacific Islander (n = 1), 84.1% White (n = 37), 4.5% Multi-racial (n = 2), and 2.3% Other (n = 1). Fifty-seven percent of the campers (n = 25) reported being on free or reduced lunch. One camper stopped attending midway through the camp and did not complete the post-survey. Therefore, forty-three participants were used in the final analysis. None of the outreach campers had attended the app camp before. Table 1 summarizes the demographic information of the two samples.

Table 2. Percentages of Unique Parent/Guardian Working in a Technical Field for Both Samples

	Father-Only% (n)	Mother-Only% (n)	Both Parents% (n)	Other
Local App Camp	30.4% (n = 21)	7.2% (n = 6)	5.5% (n = 4)	0
Outreach	16.7% (n = 5)	0	0	0

Note: These counts represent parents, because we had siblings in the App Camp.

Table 3. Previous Coding Experience of the Local App Camp and Outreach Participants (N_{local} = 98, $N_{outreach}$ = 31)

	Some Experience		No Experience	
	n	%	n	%
Local App Camp	58	59%	40	41%
Outreach	18	58%	13	42%

Table 4. Campers' Previous Coding Experience by Parents' Technical Careers (N_{local} = 98, $N_{outreach}$ = 31)

	Parent(s) in Tech	Neither Parent in Tech	Missing
Local App Camp	n (%)	n (%)	n (%)
Some Experience	20 (20%)	35 (36%)	3 (3%)
No Experience	15 (15%)	25 (26%)	0
Outreach			
Some Experience	4 (13%)	14 (45%)	0
No Experience	1 (3%)	12 (39%)	0

Note: Percentage was calculated as the proportion of each cell in the whole sample.

As studies on children's career interest development and choice of STEM (science, technology, engineering, and mathematics) careers showed that parents' occupations and their knowledge of STEM occupation related activities were important factors influencing children's interest in these fields [42, 101], we also collected information on parents'/guardian(s)' occupations and whether they worked in a technical field. Table 2 presents the percentages of parents working in a technical field for both samples, which indicates that the local app camp sample had more parent(s) working in a technical field than the outreach sample.

We also collected information on campers' previous coding experience. The local app camp participants provided this information as part of the application form. However, for the outreach participants, we collected these data during the post-camp interviews. Of note, the local app camp sample included 11 campers who repeated our camp. In addition, we only had the previous experience information for 31 out of 43 outreach campers. Table 3 summarizes the information of previous coding experience for both samples. We also conducted a cross-tabulation analysis on campers' previous coding experience with parents' technical careers. These are presented in Table 4.

4.3 Procedure and Data Sources

4.3.1 Quantitative Data. All campers took an affect survey on Day 1 (pre) and then again on the last day of camp (post). Surveys were administered via Qualtrics, an online survey software. For the purpose of this study, we only used the self-efficacy and interest scales. The self-efficacy scale was adapted from Fennema and Sherman [31]. Although we were fully aware of the different types of interest (i.e., situational interest vs. individual interest; see Section 2.3), it was difficult to differentiate them in practice as no precise measurements have been developed [82]. Therefore, we adapted Deci et al.'s [24] and Ryan's [88] scale on intrinsic motivation and Eccles and Wigfield's Self-and-Task-Perceptions Questionnaire [30], measures widely used in the motivation literature, to measure students' interest in and enjoyment of computer programming. Some of the example questions used to measure self-efficacy included "I am confident in my ability to program computers" and "I can program computers well." Sample items used to measure interest included "I enjoy computer programming" and "I think computer programming is interesting."

In addition to the affect survey, campers also completed an experience survey on the last day of camp that we designed to measure their perceptions of mentor practices. This survey reflected three aspects of mentor practices important in promoting mentees' self-efficacy and interest: mentor modeling, instruction, and encouragement. Some of the example modeling questions included "From watching my mentor, I have a better understanding of programming" and "My mentor inspired me to not quit even when programming got hard." Example instruction questions included "Mentor usually gave detailed explanations about programming concepts" and "My mentor usually encourage me to think through the problem instead of telling me the answer right away." Example encouragement question included "My mentor encouraged me to program" and "My mentor was supportive of my programming."

All the affect and experience questions were written in an 8-point Likert scale with response options ranging from strongly disagree (1) to strongly agree (8). Each scale contained several items, and we derived a composite score for each scale by averaging the item scores.

4.3.2 Qualitative Data. On the last day of camp, we conducted brief exit interviews with the outreach campers. Due to limited time, we used a cluster sample strategy to select interviewees. We first grouped campers by their mentors. We then randomly selected campers from each mentor group to secure a sample of represented experiences. One of the randomly selected campers declined to be interviewed. The total number of interviewed outreach campers was 31. The interview was guided by a semi-structured protocol focusing on how the campers felt about the camp and more specifically, how they felt about their mentors. All interviews were audio recorded and transcribed verbatim.

4.4 Data Analysis

4.4.1 Quantitative Analysis. Quantitative analysis proceeded in a multiple-stage process. In Stage One, we screened the data for possible data entry errors and univariate outliers. In the local app camp data, we found an outlier of pre- interest, a participant who was approximately four standard deviations below the group mean, $z = -3.91$. We deleted this data point and kept the rest of the participants' data. We did not find outliers in the outreach app camp group. We then proceeded to examine the distributional properties of the data. We also conducted principal component analysis (PCA) and reliability analysis to check if the data met psychometric standards.

As each set of the camps consisted of several sessions, in Stage Two, we conducted one-way factorial analyses of covariance (ANCOVAs) on the post- self-efficacy and post- interest, respectively. We used camp sessions and camper gender as factors and pre- camp scores as covariates. The purpose of these analyses was to check for possible cluster effect of camp sessions and camper gender on the variables of interest (i.e., post- self-efficacy and post- interest). In addition, we checked for the equivalence of mentor practice between the two samples.

In the last stage, we ran significance tests to examine changes from pre- to post-test within each sample, and regression analysis to compare the differences in post- self-efficacy and interest between the participants of the local app camp and outreach app camp.

Table 5. Reliabilities of Self-efficacy and Interest at Pre- and Post-Test by Groups of Participants Using Cronbach's Alpha

Construct	Sample	Pre	Post
Self-Efficacy	Local App Camp	0.88	0.90
	Outreach	0.87	0.91
Interest	Local App Camp	0.85	0.91
	Outreach	0.94	0.93

Table 6. Descriptive Statistics of Mentor Practice Scales for Both Groups of Participants and Mann-Whitney U Test (N_{local} = 81, $N_{outreach}$ = 43)

	Local App Camp		Outreach Camp		
Scale	M (SD)	Median	M (SD)	Median	p
Mentor Modeling	6.86 (1.28)	7.17	6.77 (1.67)	7.67	0.47
Instruction	6.99 (1.19)	7.33	6.94 (1.46)	7.67	0.49
Encouragement	7.16 (1.20)	7.50	6.89 (1.42)	7.50	0.36

4.4.2 Testing Measures' Psychometric Properties. Results of the PCAs indicated that both self-efficacy and interest met unidimensionality at both measurement occasions (i.e., pre- and post-test) for both groups of participants. Put differently, participants' interpretations of the two measures were consistent from pre- to post-test for both local app camp and outreach app camp participants. Table 5 below presents the results of the reliability analysis, which tested the internal consistency of a multi-item scale. All the Cronbach's alpha coefficients (i.e. indices of reliability) were greater than 0.85, suggesting that the measures of self-efficacy and interest were highly consistent across time and samples.

All the experience scales (including mentor modeling, instruction, and encouragement) were also unidimensional and reliable for both samples, Cronbach's $\alpha > 0.81$.

4.4.3 Checking for Cluster Effects. Results of the one-way ANCOVAs showed that controlling for the corresponding pre-camp scores, camp sessions and camper gender were not significant predictors of either post- self-efficacy or interest at alpha level of 0.05. In other words, participants' post- self-efficacy and interest were not different by camp sessions and camper gender. Therefore, the data for each sample were aggregated in the following analyses.

4.4.4 Checking for Equivalence of Mentor Practices. Since results of the mentor practice scales were highly skewed, we conducted Mann-Whitney U test to compare whether the two groups of participants perceived their mentors' practices of modeling, instruction, and encouragement differently. As Table 6 shows, none of the three practices showed significant difference, meaning that mentors of the two groups practiced in similar ways in regard to modeling, instruction, and encouragement.

4.4.5 Testing Changes. An exploratory descriptive analysis was conducted prior to significance tests of changes. As Table 7 presents, the local app camp sample started slightly higher than the outreach sample in both pre- self-efficacy (M_{local} = 4.59, SD = 1.73 vs. $M_{outreach}$ = 4.30, SD = 1.76) and interest (M_{local} = 6.69, SD = 1.08 vs. $M_{outreach}$ = 6.44, SD = 1.62). Although the differences in pre- self-efficacy and interest between the two samples were not statistically significant, the

Table 7. Descriptive Statistics of Self-efficacy and Interest for Both Groups of Participants at Both Measurement Occasions

		Pre		Post	
Sample	Var.	M (SD)	n	M (SD)	n
Local App Camp	SE	4.59 (1.73)	87	5.99 (1.73)	79
	II	6.69 (1.08)	86	7.75 (1.20)	79
Outreach	SE	4.30 (1.76)	44	5.51 (1.70)	43
	II	6.44 (1.62)	44	6.62 (1.54)	43

Note: M = mean; SD = standard deviation; SE = self-efficacy; II = interest.

outreach sample was more diverse in their initial interest than the local app camp participants (as indicated by the standard deviations of pre- interest, $SD_{outreach} = 1.62$ vs. $SD_{local} = 1.08$).

4.4.6 Testing Between-group Differences. We used regression analysis to test whether the camp experience had similar effects on both the local app camp participants' and the outreach camp participants' affective outcomes. The regression models specified post- self-efficacy and interest as the outcome variables, and the corresponding pre- scores as the covariate. We used a dummy variable to represent the two samples as the predictor variable.

4.4.7 Qualitative Analysis. The outreach group interview data were coded by two coders using a combination of deductive and inductive coding [77]. First, both coders looked at campers' experience, using open coding [93] strategy. As a result, all the instances where campers mention their positive, negative, or mixed feelings about the camp and or the mentors were identified. These were then coded deductively [77] as positive, negative or mixed. It is important to note here that only two campers out of 31 expressed mixed feelings towards the camp while none reported negative or mixed feelings towards their mentors. Finally, we used narrative analysis [93] to unearth nuances between different positive experiences of students. This analysis revealed that what students liked the most about the camp was coding, while mentors were liked for being approachable, helpful and motivating.

5 RESULTS

5.1 Changes in Self-efficacy

Our first research question asked about changes in self-efficacy after participating in our camps. To look for differences from pre- to post-test, we conducted paired-sample t-tests. Results showed that self-efficacy increased significantly from pre- to post-test for both local app camps, $t(78) = 6.95$, $p < 0.001$, Cohen's $d = 0.78$, and the outreach app camps, $t(42) = 4.76$, $p < 0.001$, Cohen's $d = 0.73$. This suggests that the camp experience was effective for both groups in improving their self-efficacy.

5.2 Changes in Interest

Our second research question asked about changes in interest after participating in our camps. Our data did not meet assumptions of normality, which is quite common when dealing with Likert-scale data [51]. Thus, we conducted Wilcoxon signed-rank tests. Results showed that the local app camp sample had a significant gain in interest after attending the camp, $Z = 4.78$, $p < 0.001$, $r = 0.54$. The descriptive statistics of the outreach app camp sample indicated a higher mean of post-interest ($M = 6.62$) than pre-interest ($M = 6.44$). However, the significance test showed that this difference was not significant, $Z = 0.78$, $p = 0.44$, $r = 0.12$.

5.3 Comparing Results of the two Groups in Self-efficacy and Interest

Our third research questions tested for the differences in self-efficacy and interest after attending our camps between the two samples. The result of the self-efficacy model indicated that controlling for the initial difference, group membership (i.e., whether a participant was with the local app camp or the outreach camp) was not a significant predictor of their post-self-efficacy, $\beta = -0.11$, t = −1.35, p = 0.18, with the local app camp as the reference group. This finding suggests that the camp experience did not differentially affect the two samples in terms of self-efficacy.

However, the result of the interest model showed that controlling for pre-interest differences and using the local app camp as the reference group, group membership was a significant predictor of post-interest, $\beta = -0.16$, t = −2.48, p = 0.015. This suggests that the camp experience had a differential effect on the two samples in regard to increasing their interest. More precisely, it was effective for the increase in interest of the local app camp sample. However, it was not effective for increasing the interest of the outreach sample. Possible reasons for this differential effect are explored in the Discussion section.

5.4 Qualitative Findings on the Outreach Group's Camp Experience

5.4.1 Camp Experience. We wanted to know how the participants in the outreach camps felt about their camp experience and specifically, what they thought about their mentors. All of the 31 participants expressed positive feelings towards the camp, using words such as "like" [the camp] (n = 5), "fun" (n = 17), "good" (n = 3) or "great" (n = 4), "never bored" (n = 1), and "awesome" (n = 1). When asked to explain why, most campers (n = 17) responded that they liked the coding. This ranged from finding it to be a "really fun experience," to enjoying the creation of specific artifacts (e.g., apps). The following quote illustrates one such explanations:

Camper: "I really like the coding part and making games and then messing around with them."

In other words, this camper felt that coding, and coding games in particular, was what they especially liked about the camp. That and the ability to then "mess" around with what they created was what they liked the most.

Other responses referred to the ability to personalize the apps that they made, sometimes referring to specific apps (n = 5), while the rest said "everything" about the camp was enjoyable, or they referred to camp activities other than coding (n = 7).

While most of the responses were positive in reference to the camp experience, there was one camper who liked coding the apps, but thought the content of the apps was often "boring" and wished that they could have programmed more games.

Of note, there did not seem to be any differences based on their prior experience or gender. Both boys and girls enjoyed the camp as well as youth who had prior coding experience and those who did not. For example, one boy stated that "It's fun to code 'cause [sic] [he's] never coded before. And I feel like it's fun." Similarly, a girl, who had no previous coding experience, recounted that, "[The camp]'s pretty good. Like the apps are really amazing. Coding is really great." However, another girl, who had coded before and in different programming platforms, including App Inventor and for "a long time," said:

"I just really like coding and stuff like that. And I like the drag-and-drop techniques. Like it's not too hard, but still, like hard enough for it to be entertaining."

As it can be seen from that excerpt, even youth with prior experience found the camp entertaining.

Despite the overall positive feelings towards the camp and coding, two campers had mixed feelings and expressed their dislikes. For example, one camper felt that the camp was "a bit long" but still "fun." Another camper considered the interviews that the mentors conducted after each app to be "boring":

"I like some of the coding, how we get to learn new stuff. I think some of it interests me, but others just wasn't [sic]. Because some of it just didn't interest me, because it was just like, repeating the same thing. I like learning the new things, and then just doing the same old thing just got kind of tiring to me. So, it's getting boring."

Here, we see a camper with mixed feelings. On the one hand, they enjoyed learning new things. On the other hand, they were bored by repetitive things. When probed more about what they did not like, the camper said:

"…The questions. They're so boring, you're just like, the questions like after you do them, you kind of just want to go on to the next app to do it. But you have to do the interview after and it just gets boring. So, you're just like, waiting for it to be done."

Having to talk about each app after coding it was "boring" and "tiring" for this particular camper. However, as mentioned above, despite the few negative comments, the overall sentiment towards the camp was favorable.

5.4.2 Experience with Mentors. All the campers had only positive things to say about their mentors. They often described the mentors as "nice," "fun," and "friendly." Things that campers appreciated about their mentors were their approachability, helpfulness, and ability to motivate.

As mentors were in charge of a group of five or six campers, their job was to be in close proximity to their campers. For that reason, they were perceived as being "right there" and willing to help when needed. Next, mentors were described as someone who helped them "understand more," helped them "understand how to work (...) the blocks" or someone who helped them if they needed an explanation or had a question. Finally, interactions with near-peer mentors were often motivating as the mentors shared their experience with app making and brought "positive energy" or encouraged them to keep working on their code. This is illustrated in the following quote:

"Well, it's been nice, because there are times when I get really, really tired. And he's always like, you have to keep doing it. And that helps, because he gives me the motivation I need, even when I don't want to do it."

In other words, this camper appreciated when the mentor took the time to encourage them to keep working on their code, as it was hard for them to find self-motivation when tired.

A lot of these comments came from boys talking about girl mentors and girls talking about boy mentors. In other words, we did not find that gender of the mentor made a difference in how campers perceived their mentors. The following quote is a quote from an interview with a male camper talking about his female mentor:

"Oh, she's been really nice to all the people, not just me. She's been, she's been great. Whenever I need her help, but she'll, she'll not tell me the answer. But she'll just like, lead me through it. And then I'll eventually get it. And yeah, she's taught me."

In other words, not only did he appreciate the help he received and the form it was received in (i.e., she was helping him think through the problems and not "tell [him] the answer"), but he also observed that the mentor was "nice to all people" around him. All this contributed to his positive perception of the mentor and his overall experience.

Similarly, a female camper talked equally positively about her male mentor:

"He's... he's good. Because he shows us the apps he made and tell us what to do and, and showed us a lot. So that's pretty good."

As illustrated by this quote, the male mentor was well-received by this female camper, because he was sharing his artifacts, while also helping and instructing.

In response to their feelings about the mentors, 24 of the campers were additionally asked if there was anything or anyone that they felt helped them change their coding abilities during the camp. This question was not in the original protocol, which is why seven campers were not asked this question.

Out of those who were asked (n = 24) this question, 15 specifically mentioned their mentor. Other responses included "the instructors" (n = 1), themselves (n = 1), the instructions (n = 3), "being in a group" (n = 1), learning where the blocks went (n = 1) or "I don't know" (n = 2). The majority of the campers, however, attributed their change in coding skills to working with their mentor.

6 DISCUSSION

Providing access to CS education to youth in low income areas and securing that diverse populations participate are two of the four main facets necessary for securing equity in CS education [107]. With these in mind, we designed a study that expands on existing research on self-efficacy and interest in CS, e.g., [2, 12, 14, 15, 56, 59, 96] and our own previous work, e.g., References [20, 21]. While numerous studies have been designed to affect youths' attitudes towards CS, e.g., [74, 86, 90, 103], our review shows that there is still no definitive conclusion on what design features are effective in improving self-efficacy and interest. Furthermore, there is also lack of evidence to show the efficacy of some design features that proved to work for one population is transferrable to another population. In this study, we compared the effects of our camp on the affective attitude of youths from two different populations: one representing the local community and the other representing youth with diverse ethnic/racial background and from low-income high-poverty areas.

One primary goal of the present study was to investigate the effects of our camp design on self-efficacy. Our findings showed that our camp design was effective in increasing self-efficacy for both samples. This result is consistent with our previous studies, where different cohorts of participants in the local app camp improved their self-efficacy after attending the camp (see [18, 21]). In addition, the present study confirmed the effectiveness of our camp in improving the self-efficacy with a diverse population of youth. While we did not specifically ask about self-efficacy, the majority of the outreach campers attributed their growth in coding skills to their mentors. The mentors provided support, help, and were approachable, which are possible reasons for the significant increase in self-efficacy. This aligns to previous research that found mentor support [21], mentor relatability [19], and mentor modeling [99] were related to increases in self-efficacy.

Despite its comparable effects on the two samples in respect to self-efficacy, the present camp design affected the interest of the two samples in slightly different ways. The app camp participants reported a significant gain in interest whereas the outreach participants reported gain in interest, but it was not significant. To explain this difference, we compared the quantitative findings to qualitative findings. The comparison revealed a congruity in terms of mentor practices and camp enjoyment. Specifically, there was no statistical evidence indicating that mentors of the two camps approached the campers differently. However, the qualitative finding showed a positive and beneficial mentorship between the outreach campers and their mentors. Additionally, there was also qualitative evidence showing that regardless of their prior coding experience, the majority of the outreach campers enjoyed the camp and coding, which is congruent with the high interest observed in the post-camp test (Outreach $M_{post} = 6.62$).

Given these findings, the reason for the non-significant interest gain is most likely due to the self-selection bias between the outreach and local app participants in terms of their initial interest. While in most cases, parents signed the local app camp youth up, the outreach participants were exclusively recruited by schoolteachers. This means that the local app camp participants were likely to start with a maintained situational interest or even an emerging individual interest, while some of the outreach participants might have started with little interest. Specifically, our data showed that compared to the outreach youth, more of the local app camp youth were from families where one or both parents had a technical background. This may mean that the local app camp youth had more resources from the perspective of interest development than the outreach youth. For the former, attending our camp was only another way they used to maintain an already existing interest in CS. According to Hidi and Renninger [46, 82], when interest is maintained through repeated engagement, it is easier to deepen or evolve into a higher state of interest, which may be why we are seeing a significant increase in interest for this particular group.

However, our data showed that compared to the local app camp participants, fewer outreach participants had both prior coding experience and a parent working in a technical field. To say it differently, of our outreach participants, 39% had neither previous coding experience nor a parent working in a technical field compared to 26% of the local app camp sample (see Section 4.2.3). As Hidi and Renninger [46] noted, interest is the outcome of an interaction of person, content, and environment, and content and environment contribute to interest development. There is also research that indicates when parents value something their children tend to value it too, which can then lead to interest development [44]. For example, having conversations about the value of CS and the opportunities afforded by studying CS, parents could influence their child's value and potential interest in CS [18, 44]. Therefore, not having parents who work in a technical field, not having parents who knowingly seek CS opportunities, or not having parents who model CS values in addition to not having access to CS in their daily life are potential barriers for youth to develop an interest in CS. Note that this is not a comment on the parents or guardians. Another way to consider this is that when parents lack access to resources their children may also lack access to resources. While we try to model the value of CS in our camp activities and show videos of relatable models talking about their experience in CS, for 39% of the youth in the outreach camp, our camp was their first exposure to these ideas. As the descriptive statistics show, the outreach youth reported more variability in their initial interest, with some youth reporting lower interest than others. This means that at least for some of the outreach youth, it requires more effort to trigger their interest compared to those with prior experience. In other words, since our camp was only five-days long, more exposure may be needed to trigger the interest of those who are in the incipient phase of interest development. Furthermore, the qualitative data indicated that most of the outreach youth enjoyed the camp and coding, which suggests that our camp had promoted a situational interest among the outreach youth. However, this interest may not be stable in its early stages of development. For example, Scaico et al. [95], in their research on trajectories of interest in a programming class, found that interest can be "volatile at the initial phases of its development and responsive to what comes from the environment" (p. 20). Recall that one of the campers liked "some of the coding" but did not like talking to their mentor about their app after they finished coding, because it was "boring" and "tiring."

Our findings on the increase in self-efficacy and interest among the outreach group (although the latter was not significant) indicate that the camp design has the potential to promote a positive affect among youth from low income high poverty areas. Also, as Bandura [9] noted, there sometimes is a temporal lag between self-efficacy and interest, meaning that a high sense of self-efficacy does not lead to an immediate change in interest. However, with multiple exposures in the future, we believe, this positive feeling can transform into a genuine interest, which emphasizes the importance of providing access to CS education opportunities in low income and rural areas (see [107]).

6.1 Implications for Future Design

To promote interest for youth who do not self-select to participate in CS, we may need to better design to the needs of participants with lower initial interest. Harackiewicz, Smith, and Priniski

[45] proposed four interest-enhancing strategies: attention-getting settings, contexts that evoke prior individual interest, problem-based learning, and enhancement of utility value (i.e., perceived value of an activity). We describe how some of these strategies could be used in camp design below.

Our camps run for 3 hours a day over a 5-day period. We condense a lot of coding and debugging practices into the week. There are some social activities, but the emphasis is placed on coding the apps. While some campers are very content with coding for 3 hours straight, it could be that initial stages of interest development are better supported by shorter coding sessions over a longer period of time. Or, if limited to a camp-like structure, then each day could be broken up with activities away from the computer such as playing with interactive apps or engaging in unplugged activities around coding that can offer other entry points into coding concepts (e.g., tabletop games). Also, while we allow for personalization of apps, we designed a curriculum where campers follow a sequence of apps. While we have a lot of options for more advanced coders to stray from this curriculum, we could build more choices into our curriculum sequence that allow emerging coders to make choices about possible apps to code in the initial stages of interest development. This could involve dividing the content into concepts and providing choices of two to three different apps and creating a branching structure of apps rather than our current model that is more linear. Or rather than a few simple apps that get at multiple concepts, allow youth to engage in interest driven app design [5, 79].

In future research, we would like to run some focus groups with youth in the outreach program and find out more about their interests and how we can build connections between their lives and what we do in the camp. If we help them see the value in what they are doing and how it relates to their lives, then we may be more successful in increasing interest.

7 LIMITATIONS AND FUTURE DIRECTIONS

Our study has a few notable limitations. First, we only looked at the immediate camp effects on the participants' self-efficacy and interest. Future studies could focus on the camp's long-term effects, that is, whether the high sense of self-efficacy and interest is sustained over time and/or whether interest evolves into a higher state. Second, our study only investigated the effectiveness of our camp design from a holistic perspective. Local experiences of individual campers, such as what the learning processes of campers of different backgrounds were like or whether the curriculum was accessible to all the campers, could be explored to advance the understanding of our camp design to different populations. This would involve an intersectionality approach that accounts understanding of individual experiences while also taking into account systems of inequality, e.g., [100]. Third, while we have placed an emphasis on self-efficacy and interest, we have not explored camper's sense of belonging in CS (which is related to students' affect) and whether they feel accepted and valued, e.g., [66].

8 CONCLUSION

Broadening participation in CS is still a national priority [72]. In this research, we showed that our camps were successful in increasing participants' self-efficacy, but there is still work to be done to increase interest of youth who come from low income high poverty areas, where access to CS education opportunities is limited. Whether through informal programs or formal school settings, we need to design experiences that allow youth to build connections between their lives and CS. If we help youth see the value in what they are doing and how it relates to their lives, then we may be more successful in increasing interest.

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