Recruiting Practices in Informal CS Learning

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Introduction: Computer science (CS) lacks representation from people who identify as one or more of the following identities: woman, Black, Indigenous, Hispanic, Latina/Latino/Latinx, or disabled. We refer to these groups as historically underrepresented groups (HUGs). Informal learning, like CS summer camps and hackathons, can increase interest in K-12 students but still struggles to broaden participation. Objectives: In this study, we examine one source of struggle for informal learning programs: recruiting practices. Methods: Toward the goal of understanding this struggle, we interviewed 14 informal K-12 CS learning programs across a diverse region in the Northwestern United States to understand what recruiting practices are being used. We used a cultural competency lens to examine the variation within recruiting practices and how some practices could lead to broader participation in computing. Results: We identified 18 different recruiting practices used by informal CS learning program organizers. Some programs had similar practices, but subtle differences in implementation that led them to fall at different points on the cultural competence continuum. More culturally competent implementations generally involve reflection on the needs of specific populations that programs were trying to recruit, on why previous recruiting implementations did not work, and on feedback from stakeholders to change their implementations. This is the first article to investigate how the implementation of the recruiting practice determines its cultural competency. Conclusion: Results from this study illuminate some of the problems informal CS programs face in broadening participation in computing and provide insights on how program organizers' can overcome them. Our work highlights how students or parents access resources, the challenges program organizers encounter, and whether current recruiting practices effectively engage students from HUGs.

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

Additional Key Words and Phrases: Informal learning programs, Broadening Participation in Computing, K-12

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1 Introduction

Computer science (CS) does not have proportional representation of people from **historically underrepresented group (HUGs)** in computing [5, 8, 12, 53, 55, 58, 67, 68, 69]. More than 80% of students who graduated with a bachelor's degree in CS in 2016 were male; 48% of those who graduated with their degree were white, 24% were Asian, and the next highest group to graduate with their CS degree were non-U.S. residents, which made up 12% [83]. The lack of proportional

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diversity results in a variety of problems. For example, low representation of people from HUGs in CS can decrease a software team's ability to solve complex problems [66] and result in biased software that disproportionately negatively affects people from HUGs [44, 50, 76]. If computer scientists are to equitably produce useful software, advance science, teach future generations, and influence policy, they must have diverse identities, experiences, and cultures that reflect society [66].

People from HUGs face many barriers throughout CS. For example, students from HUGs often experience unwelcoming climates and cultures in CS, which may diminish their sense of belonging in CS [8, 53, 64, 74, 77]. Prior literature reports a myriad of environmental factors that correlate with a low sense of belonging in students from HUGs in CS. Some of these factors include negative peer-to-peer or instructor interactions [34, 36], a lack of same-race and gender role models [38], stereotypes of who belongs in CS [38], and a lack of collaboration [51, 67]. Another barrier is that some youth from HUGs tend to have limited access to computers at home and CS classes at school [54, 55, 62, 67, 77], despite most of their parents wanting them to learn CS [77].

Informal CS learning programs, which include activities like after-school clubs, summer camps, and hackathons, can expand students' access to CS when their formal learning opportunities are limited. These informal CS learning programs can increase interest in CS among students from HUGs [7, 10, 26, 30, 37]. Some informal CS learning programs aim to be more inclusive of people from HUGs, like girls of color [37, 39, 63, 72]. Another way programs aim to be more inclusive is by designing their curriculum with elements of social good or culturally relevant themes [11, 28, 30]. Despite the focus on inclusion, informal CS programs tend to lack proportional representation of students from HUGs [27, 56, 67]. Unsurprisingly, most of the youth who enroll in informal CS learning programs are white boys [27].

Prior work has examined why informal CS learning programs tend to lack participation from students from HUGs. Some research points to the same sense of belonging issues students from HUGs face in formal CS classes [56, 70]. Other research has suggested that informal CS learning programs can be hard to access: the search terms used by parents of students from HUGs to find such programs for their kids tend to yield unproductive results [29]. Some research suggests that people from HUGs do not participate in these programs because they are not interested in them [11, 15, 37]. Prior research has also examined how the financial costs of informal CS learning programs can prevent both parents from enrolling their child and potential organizers from hosting them [32, 37]. Notably, there is prior work offering guidance to potential organizers on how to plan and fund these programs to increase **Broadening Participation in Comupting (BPC)** efforts [10, 30].

While prior work has carefully examined economic, student, and family factors, fewer works have examined the role that the recruiting practices used by informal CS learning programs play in shaping the representation in these programs of youth from HUGs. Recruiting practices, for example, shape how information is disseminated and who might be able to access that information. Variations in the implementation of recruiting practices likely shape the *cultural competence* [21] of the recruiting practice. Cultural competence is when systems align their attitudes and policies to enable them to work effectively in cross-cultural situations [21]. Therefore, in this article, we ask the following questions: *What are the recruiting practices informal CS learning programs use?* and *How is the cultural competency of informal CS learning programs' recruiting practices shaped by the variation in their goals and implementation of their practices?*

To answer these questions, we conducted semi-structured interviews with people from 14 different informal CS learning programs across the Northwestern United States. We asked them about their recruiting practices, who attends their programs, what they do to support diversity, and the challenges they face in broadening participation. We examined the data through a cultural competence lens to understand the variations in recruitment practices. Our results provide new insights into the subtle, but often important, structural choices that need to be considered when implementing recruiting practices because these practices likely shape who engages in informal CS learning.

2 Background Literature

Recruitment, as a way to broaden participation in CS is a challenge across all levels of education. Some of the research on recruiting practices [3, 19, 47, 65] in CS focuses on recruiting high-school women to undergraduate CS programs. Some prior research offers insights into how teachers can recruit students for formal K-12 education, which is ages 6–19. However, there is little research on how informal CS learning program organizers could recruit students. We will start by discussing some of the recruiting practices that prior work has recommended in the undergraduate, K-12 (ages 6–19), and informal CS learning spaces. Then, we will briefly discuss some of the prior research around **Science, Technology, Engineering, and Math (STEM)** informal learning spaces.

Research [3, 9, 19, 47, 65, 81, 82] provides recommendations for recruiting high-school girls and undergraduate women to take CS courses throughout their undergraduate degree, much of these recommendations are synthesized by Cohoon [20]. Some of the recommendations include: "work with high-school teachers," "communicate with high-school guidance counselors," "use role models to actively recruit high-school students," "offer multiple points of entry," and "make contact with the local community" [20]. Another way undergraduate programs recruit women to their CS degree program is by inviting them to computing conferences like Grace Hopper [3].

Wu et al. [81] is the only study that we know of that investigated the recruiting strategies and outcomes of seven computing departments. They found that departments that implemented the following five recruiting strategies saw increases in the number of women who applied to their CS department. These departments provided high school girls who declared a CS major with scholarships, advertised the CS major with inclusive languages and images on department websites, social media, and printed materials, created multiple pathways for students to transfer into the major, conducted K-12 outreach programs that focused on hands-on activities, and used faculty and student ambassadors in outreach events that focused on engaging potential students and their guardians [81]. As we will discuss in the results, some of the recruiting practices undergraduate CS departments use could be and sometimes are applied in informal CS learning programs.

While many works have examined how undergraduate CS programs recruit students from HUGs, one point of comparison is the recruiting practices of in-school K-12 CS learning programs. K-12 schools can recruit students from HUGs in computing by hosting workshops for teachers that inform them of the importance of engaging more youth in CS, as well as giving them some strategies for doing so [18]. Teachers can recruit students to formal K-12 CS classes through purposeful small-group recruitment, which is when they seek out and inform small groups of students who they think might be somewhat interested in CS [40, 41]. By encouraging groups of students who are from HUGs in CS to pursue the topic, these students seemed more likely to develop a sense of belonging in the CS courses [41]. Like undergraduate recruiting practices, K-12 recruiting practices do not have to be unique to the K-12 context, informal CS learning programs could use some of these practices to further bolster their recruiting efforts. However, we do not currently know to what extent informal CS learning programs use these practices. Also, it may be hard for informal programs to recognize the potential for applying these strategies since the recruiting practices mentioned are typically used in different contexts.

Prior research [1, 17, 49, 73] offers recommendations for how informal learning programs may enhance the recruitment of students from HUGs. One strategy involves brokering learning opportunities through a two-step process of advertising small hands-on workshops in multiple locations, then connecting students from these workshops to foster a stronger sense of community.

Another example of a brokering strategy is to advertise that former students help teach newer students. This gives younger students a chance to have role models [17]. Programs could also advertise taking students on field trips to computing-related locations which could give students connections to further CS opportunities [17]. All these practices get students involved in CS, build their social capital by connecting them to larger groups of peers, and further develop their interest in CS by sharing resources that they may have otherwise not had [17]. Social capital was defined by Lin [52] as the "resources embedded in social relations and social structure which can be mobilized when an actor wishes to increase the likelihood of success in purposeful actions." While these practices that build students' social capital are benefits of participating in the program, these benefits could be advertised through recruiting practices. Also, Akiva et al. [1] suggested that if programs want to recruit students from HUGs in CS they should consider hosting their programs in local communities rather than at colleges or museums. Then, Groth et al. [42] recommended that informal CS learning programs advertise that they provide financial aid so that they could encourage students from HUGs in computing to attend their program. There is also research on the recruiting practices used by informal STEM learning programs outside of CS [6, 46, 61]. Jeffers et al. [46] looked at 59 STEM outreach programs and discovered that the most common way these programs recruited students was by directly reaching out to K-12 schools. Prior literature would suggest that the process of recruiting students by contacting K-12 schools is common and not unique to formal or informal learning programs [6, 20, 46]. Bachman et al. [6] ran a STEM summer camp targeted at students from rural communities who might be interested in STEM and recruited students through direct mail and personal contact with secondary school teachers. Also, another way STEM programs recruit students is if the program was hosted on a college campus, one way they could recruit students is by partnering with other STEM programs on campus and asking them to tell their students about the other STEM summer programs they could enroll in [60]. This technique of partnering with other programs or organizations is one that has been used by undergraduate CS departments [20] and informal CS learning programs [17].

While there has been extensive research on recruiting practices at the undergraduate [3, 20, 22, 48, 71] and K-12 level [18, 40, 41], these practices have limitations that informal CS learning programs may be able to avoid. One limitation of undergraduate programs is that by the time students arrive on college campuses, their perceptions and stereotypes of CS may prevent them from taking introductory CS classes [16]. Then, K-12 schools are typically limited by their resources and knowledge of how to balance the tradeoffs of CS curricula and other classes. Specifically, whether they have the resources to fund CS teacher development [35] and how including CS courses in the K-12 curriculum could reduce students' involvement in other classes like history and English [79].

Informal CS learning programs may be able to avoid these limitations because they typically are focused on students between the ages of five and eighteen, tend to already have staff trained in teaching CS, and typically do not have to worry about providing a holistic educational experience. However, as mentioned in the previous section, few works have examined the role the recruiting practices used by informal CS learning programs play in shaping opportunities in broadening participation in computing.

How recruiting practices are implemented determines how informal CS learning programs market to youth, who to partner with, what programming to offer, and more. These choices in implementation and their possible impact on participation are shaped by variations in the recruiting practices' *cultural competence* [21].

3 Theoretical Background: Cultural Competence

What recruiting practices are used by informal CS learning programs and how they are implemented, shapes what resources to provide, where to reach students, and how to reach students. However, decisions regarding how and why to recruit have not yet been examined through a critical lens. In order to start understanding how the recruiting practices used by informal CS learning programs play a role in shaping who may engage in informal CS learning, we use the lens of cultural competence.

Cultural competence is defined by Cross et al. [21] as:

> "A set of congruent behaviors, attitudes, and policies that come together in a system, agency, or amongst professionals and enables that system, agency or those professionals to work effectively in cross-cultural situations. The word culture is used because it implies the integrated pattern of human behavior that includes thoughts, communications, actions, customs, beliefs, values, and institutions of a racial, ethnic, religious, or social group."

Cultural competence has been used as a framework in a variety of disciplines. Originally, cultural competence was developed in the 1980s and used by social workers and psychologists [80]. It has since been adopted by other disciplines like education and health care as a way to provide more culturally mindful learning and health care experience [2, 13, 25]. The framework has also been used in CS as a way to outline what a potential culturally competent CS department might look like [78]. Also, as a way to design an artificial intelligent class in primary school [69].

The word "competence" is used to illustrate a continued effort to know and learn more about the communities programs work and interact with. Several works have added nuance to this perspective. For example, work on cultural *humility* accounts for systemic structural barriers that can influence people's opportunities and experiences [33]. Other work demonstrates that competence is not a binary, but multifaceted [75], in part due to the idea that no one can be completely competent in another group's culture [59]. Furthermore, focusing on "competence" can also highlight the need for organizations to question their own beliefs, biases, and assumptions about other cultures [23].

3.1 Elements of Cultural Competence

As originally defined, cultural competence has several elements. We review them here and illustrate ways that they might manifest in informal CS learning program's recruiting practices.

3.1.1 Valuing Diversity. One element of cultural competency is valuing diversity. Diversity can consider many aspects of a person (e.g., gender, age, ability, race, ethnicity, religion, and sexual orientation). When programs are able to value diversity, they are able to understand that people make decisions based on their background and culture [21]. When programs are able to accept that different cultures value different things, they can better interact with cultures other than their own. For example, some of the youth from HUGs in CS value applications of computing that focus on doing social good, so programs that relate their activities to social good are demonstrating value of diversity [11, 15].

3.1.2 Cultural Self-Assessment. Cultural self-assessment is the ability of programs to evaluate whether practices align with their beliefs. An example that does not demonstrate cultural self-assessment would be a CS learning program believing that they are trying to narrow the gender gap, but not implementing recruiting practices or programs that would appeal to girls or non-binary students. Oftentimes, it is challenging to identify biases in one's practices and beliefs. However, when programs understand how their beliefs are shaping their practices, then it should become easier for them to assess how they are interacting with other cultures [21].

3.1.3 Dynamics of Difference. Dynamics of difference is "*when a system of one culture interacts with a population from another, both may misjudge the other's actions based on learned expectations*" [21]. Managing cross-cultural communication takes more than good intentions because each culture brings their own identity, stereotypes, etiquette, and problem-solving strategies to the relationship. This requires programs to be aware of potential cultural misinterpretations and misjudgments. For example, a CS summer academy that was focused on increasing the representation of deaf and hard-of-hearing students hired American Sign Language interpreters as a way to help manage communication between instructors and students [14].

3.1.4 Institutionalization of Cultural Knowledge. Institutionalization of cultural knowledge is when programs implement ways to learn and preserve knowledge about cultures other than their own [21]. When programs are able to do this, they can mitigate problems that might come up due to ignorance. Institutionalization of cultural knowledge is also a continuous process that should involve developing and maintaining connections to the cultures a program is trying to serve. If an informal CS learning program held quarterly community panels with members from HUGs in order to understand where they could improve, they would be institutionalizing cultural knowledge.

3.1.5 Adaptation to Diversity. Adaptation to diversity is when programs change their policies and practices in order to meet the needs of people from different cultures [21]. Informal CS learning programs serve people from a variety of cultures, which means that they serve people with different experiences and beliefs. For example, Bryant et al. [11] designed their curriculum to better engage students from HUGs by incorporating paired programming and personal projects centered around data science for social good.

3.2 Points on the Cultural Competence Continuum

Cross et al. [21] described a continuum of six levels of competence. Here we describe examples of how these different points might manifest in recruiting practices by informal CS learning programs.

3.2.1 Cultural Destructiveness. Cultural destructiveness is the least competent level. This point "is represented by attitudes, policies, and practices that are destructive to cultures and consequently to the individuals within the culture" [21]. Some examples of cultural destructiveness are ableism, racism, homophobia, and sexism. In an informal CS learning program, this could look like instructors telling their students that girls do not belong in CS because they cannot code as well as boys.

3.2.2 Cultural Incapacity. The second point on the continuum is cultural incapacity. Programs that are at this point on the continuum are unwittingly agents of oppression [21]. For example, their practices reinforce stereotypes whether they are aware of it or not. Besides reinforcing stereotypes, examples of cultural incapacity could include instructors having lower expectations of students from underrepresented groups, or implicit messages to them that they are not valued [8].

3.2.3 Cultural Blindness. Cultural blindness is the midpoint of the continuum and is characterized by the belief that the identities and culture of a person makes no difference in the opportunities they have. Programs at this point typically believe they are unbiased, encourage assimilation to the dominant culture, and ignore cultural strengths [21]. An example of this would be if an informal CS learning program attributed the lack of diversity at their camp to defects in students instead of determining whether or not they were reaching those students. Due to unbiased beliefs, it is not uncommon for programs at this point to try and implement projects for underrepresented students (e.g., a girls-only CS class), but be unsuccessful.

3.2.4 Cultural Pre-Competence. Cultural pre-competence is the fourth point on the continuum. Informal CS learning programs at this stage might realize their weaknesses in serving students from HUGs in computing and then attempt to improve their services in some aspect. This point might also be characterized by informal CS learning programs trying to hire a more diverse staff, implement equitable recruiting practices, and teach staff about cultural competence. However, programs at this point may succumb to a false sense of accomplishment and tokenize underrepresented staff members or students they serve [21]. An example of a culturally pre-competent CS summer camp is one reported in prior work that focused on recruiting Latina/o/x youth by incorporating culturally relevant themes into their curriculum [37].

3.2.5 Cultural Competence. Cultural competence is the fifth point on the continuum and is characterized by the implementation of all the elements of cultural competency. Informal CS learning programs at this point might commit to implementing practices and policies that create and support an inclusive environment [21]. For example, DeWitt et al. [28] reported on a culturally competent CS summer camp, which focused on trying to change the stereotypical perceptions of who is a computer scientist. Involving local 5th - 9th-grade students in their program and incorporating computing for social good topics into their instruction, while measuring impact on students' self-efficacy and attitudes [28].

3.2.6 Cultural Proficiency. The last point on the continuum is cultural proficiency. Informal CS learning programs at this point might be constantly looking for ways to improve their practices and policies through research and feedback from community stakeholders. Informal CS learning programs might systematize cultural competence throughout their program by evaluating their policies and practices and making adjustments that are based in research. These programs advocate for systematizing cultural competence [21].

4 Method

With cultural competence as our frame, we return to our research questions: What recruiting practices are used by informal CS learning programs? And, How are the cultural competencies of informal CS learning programs' recruiting practices shaped by their goals and implementations? To answer these questions, we conducted semi-structured interviews with 14 people involved in informal CS learning programs across a geographically, ethnically, and socioeconomically diverse region in the Northwestern United States and used thematic analysis to analyze the discussion of recruiting. We focused on the Northwestern United States because of our access to the community and the abundance of informal CS learning programs in the region. The region's abundance of technology companies added additional organizational diversity, as some were funded by companies or offered directly by companies. All of our procedures were reviewed and approved by an independent human subjects ethics review panel.

4.1 Positionality

In this positionality statement, we aim to describe the professional and personal biases that may have influenced how we, the authors, conducted the research. We follow recommendations from Holmes [45] on how to write a positionality statement and take a reflexive approach. We believe that BPC is important and that we, the researchers and those who do CS education research, need to examine the ways in which CS education is inaccessible, inequitable, and unjust. Additionally, we believe that one way to determine the ways in which CS education is inaccessible, inequitable, or unjust is by understanding the extent to which the systems that makeup CS education are intentionally considering the variety of values, perspectives, and goals that different groups and people from HUGs have. When systems of an institution do not intentionally consider people's values, perspectives, and goals, they make it much harder, and likely impossible, to create a system that is accessible, equitable, and just.

The belief that we cannot create an accessible, equitable, and just CS education system without direct intention guided our selection for the cultural competence framework. We selected cultural competency because it gives researchers a lens to understand how institutions are serving and considering the different values, perspectives, and goals of different people who are from groups historically underrepresented in computing.

The research team was composed of three researchers with varying levels of research experience and different sociocultural identities. At the time of the study, the first author identified as an able-bodied white man and undergraduate CS researcher with three years of qualitative research experience; the second author, a Black woman and an undergraduate student studying interaction design with over a year of academic research experience; and the third author, a biracial woman who is a professor at a university in the geographic area where our study took place.

The team's varying levels of research experience and different sociocultural identities likely influenced all aspects of the study design. For example, as noted earlier, the first author is an able-bodied White man. Therefore, he likely could not understand or identify all the ways in which the recruiting practices used by informal CS learning programs are not meeting the needs of people from different HUGs. However, the other authors are from groups that are historically underrepresented in computing. While no one person can speak for entire groups of people, the different perspectives that each author provided made the team's iterative discussions of the themes that emerged through our coding process that much more important. These discussions enabled us to develop a deeper understanding of how the cultural competency of informal CS learning programs' recruiting practices is shaped by their implementation.

The research team was made up of what Holmes calls, "insiders" and "outsiders" [45]. The first and second authors were outsiders. Those members of the research team had no connection to the informal CS learning program community. When compared to an insider, the lack of prior connection to the community we were investigating may have made us more stoic when analyzing how the variations in the implementation of a recruiting practice shape the cultural competency of a particular recruiting practice. This is because our perspective on the implementations of their recruiting practices was as researchers, not as people who are in the community. The third author was an insider in the community. She studies CS education and directs a statewide K-12 CS education advocacy coalition, and is known by many of the participants in our study. Since one member of the research team was an insider we were more easily able to contact people who could participate in our study and provide meaningful insights into our research questions. Additionally, having an insider on the team may have helped us design a more meaningful interview protocol because she was able to use her prior knowledge of informal CS learning programs to help shape the questions we asked participants. Lastly, since many of the participants knew her and shared their experiences with us they likely trusted her. As such, the experiences the participants shared with the interviewer, who was the first author, may have been more honest.

4.2 Sampling

We began sampling by building a list of informal CS learning programs to contact. Our inclusion criteria included (1) programs that had to focus on developing interest in CS with youth and (2) programs that had to focus on youth in the Northwestern United States. We used four sampling methods:

- We drew upon our prior knowledge of local informal CS learning programs, which consisted of a community of educators and K-12, which is ages 6 through 12, advocates who either ran CS programs themselves or knew of others who did. This method resulted in the first eight programs being added to our list to contact.
- We contacted third-party vendors and asked them for the contact information of any CS programs in the Northwestern United States. Third-party vendors are online websites that advertise a variety of after-school activities and programs. We discovered through our local

sources that informal CS learning programs sometimes use third-party vendors to advertise their program which is why we contacted the vendors directly. This method resulted in four programs.
—We searched the web for informal CS programs in the region using these search terms: "CS summer camps," "CS summer camps," "after school CS program," "after school CS programs," "after school CS classes," and "after school CS classes." Even with the help of the internet, almost all of the programs on our contact list were concentrated in a specific region of the Northwestern United States. This revealed an additional 23 programs.
—We used snowball sampling, asking participants for recommendations as the last sampling technique. Many of the programs that the participants named were already on the list of programs to contact. However, through snowballing we were able to reveal one additional program.

Our final list of 36 programs is likely not a comprehensive list, but it does likely represent a range of programs along urban/suburban/rural, for-profit/not-for-profit, and targeted/general axes.

4.3 Participants and Procedures

We recruited by email and sent a recruitment email to all 36 programs. The email included information about who the researchers were, why we were contacting them, what the study was about, what they would get out of the study, a link to our informed consent, and an estimate of how long the interview would take. We also informed them that they could do the interview asynchronously over email or via Zoom since at the time of the study there was widespread protest across the U.S. and COVID-19.

Of the 36 programs we contacted, 16 responded and 14 of them participated. They were a mix of urban, suburban, for-profit, not-for-profit, specifically targeted, and generally targeted programs. The 22 programs that did not participate either (a) reported that they were not offering courses due to COVID-19 and felt that they could not provide the information we were looking for, (b) never replied, (c) or gave no reason.

Our sample of program representatives included a mix of informal CS learning program directors, coordinators, and CEOs. The resulting sample of organizers included six men, three women, and five people who preferred to not disclose their gender. We had participants who responded to the survey report that they were Asian, white, that the question was not applicable, or other.

We developed a twenty question protocol for our semi-structured interviews. The questions focused on:

—The kinds of recruiting practices they used
—The gender, racial, and socioeconomic diversity of the students who participated
—The problems their program faced when it comes to broadening participation in CS
—What they do to broaden participation in CS

We collected many examples of the kinds of recruiting practices used, why they were used, and how they were used. However, we were unable to collect substantial data on the diversity of staff and students at the programs because few informal CS learning programs collected that data themselves.

We piloted and iterated on our question set with the help of someone who had run an informal CS learning program in the past. Since we were not offering any financial incentives to participate in our study, we aimed to keep the Zoom interviews within 30 minutes. With permission from the participant, some of them took longer. Once the interviews were completed, we downloaded recordings, deleted them from the platform, transcribed them, and removed any identifiable information from the transcript.

4.4 Data Collection

Before conducting interviews, we manually collected data that could give us a sense of what their program was focused on. To this end, we collected data about age groups, costs, populations they aim to serve, length of the program, whether they were for-profit or non-profit, the coding languages taught, and the type of informal CS learning program they were. We also collected data that showed evidence of our participants using recruiting practices, such as which social media platforms they used to triangulate with the data from the interviews. After the interviews were conducted, we looked back at the program website data to better understand our first research question. We specifically looked at the recruiting practices participants reported using in the interview and the recruiting practices participant's websites reported using. Our triangulation efforts showed that there was a large overlap between the recruiting practices on participants' websites and what participants reported in the interviews. As should be expected, the interviews provided more context into how and when certain recruiting practices were used. However, there were times that the data we collected from participants' websites contextualized what participants reported in the interviews. For example, participants did not always report the overall mission and goal of their programs during the interviews, but on their websites their mission statement and goals were clear.

4.5 Data Analysis

Our qualitative analysis followed the guidelines of Hammer and Berland [43]. Therefore, we treated the results of our qualitative coding as thematic claims about the data rather than treating the codes as quantitative data. This means that we do not report on the number of times a code appeared in our data, and do not report inter-rater reliability measurements; rather, we focus on emergent themes in the data for further investigation and the disagreements that we encountered and resolved when interpreting data as a group.

Our unit of analysis was *recruiting practices*. We defined recruiting practices as ways informal CS learning programs spread awareness about their program and the incentives they provided students to attend. In order to analyze the recruiting practices, we systematically read each participant's transcript and website, identifying all sentences referring to recruiting practices. We then open-coded the sentences and identified twenty-eight distinct types of recruiting practices. Through iterative discussion and refinement of these recruiting practices, the first and second authors revised a more accurate list of eighteen. There were no significant disagreements during the revisions. Then, we performed axial coding of the entire set of sentences relating to recruiting practices, systematically assigning sentences from the categorized types of recruiting practices to elements of cultural competency. Our analysis revealed that variations in implementation that made the same recruiting practice fall on different points on the cultural competence continuum.

5 Results

To answer our research questions we illustrate recruiting practices by providing and discussing quotes from the participant interviews. The IDs attached to each quote represent the participant (i.g. P3). To illustrate the cultural competency of each recruiting practice we discuss the variations and nuances in the reasons, goals, and follow-through of why and how informal CS learning programs implemented the practices.

The recruiting practices we choose to discuss in this article either were implemented by informal CS learning programs in different ways or were generally more culturally competent. This allows us to illustrate how the cultural competency of a recruiting practice is shaped by the nuances in the implementation and provides positive examples for practitioners and researchers.

5.1 Cultural Incapacity

Cultural incapacity in recruiting practices perpetuates stereotypes about who engages in computing, maintains access for those already privileged in computing, and makes assumptions about why some students don't participate in offered programs. Recruiting practices that demonstrate cultural incapacity typically do not demonstrate valuing diversity or any of the other four elements of cultural competence. In this section, we will discuss how programs implemented different recruiting practices that seemed to demonstrate cultural incapacity.

5.1.1 Justifying Higher Price Points. A few informal CS learning programs' reasons for implementing some recruiting practices were to justify their high cost of attendance. When informal CS learning programs used recruiting practices in this manner, they likely excluded students from participating and may have continued to provide access to computing to people who already know about or have access to computing. One recruiting practice informal CS learning programs used to justify higher price points was by hosting programs at universities. P3's website advertised that all their classes took place on a college campus. When talking about why they focus on hosting programs on college campuses P3 explained:

> *"Traditionally we've been very University focused because of a few reasons. One, the prestige and, two, the experience that we're selling. The experience that we're selling is this: hey, you know, come experience life on the university campus stay in the dorms... so we've really been focused on that."* (P3)

P3 seemed to justify the high cost of attendance through their recruiting practice of hosting their program on college campuses because of the prestige and experiences college campuses offer. Note that the website of the informal CS learning program that P3 represented reflected that they are *"University focused"*. Additionally, P3 explained that *"[We're] looking for people with intent... That means that we targeted people with more means, more financial means."* Conflating the ability to pay with intent could reinforce the idea that to gain access to CS you need to be wealthy [54]. Students who may have been interested in their program were likely denied access because they did not have the *"financial means"* (P3), and to P3 that could mean they did not have the *"intent."*

5.1.2 Filling Enrollment. It was not uncommon for informal CS learning programs to design their recruiting practices to fill enrollment. When informal CS programs failed to adapt their practices for the different student populations they aimed to serve, they may have inadvertently excluded those populations through their recruiting practices.

Some programs implemented the practice of social media in ways that demonstrated cultural incapacity. For example, at the time of the interview, P10 reported that their program mainly used Facebook, Instagram, and Nextdoor, which aligned with the social media sites they advertised on their website, to recruit students. P10 reported that they would have preferred to implement other forms of recruitment, like *"hard-copy flyers"* (P10), similar to what they had done in the past.

However, P10 explained that their old process of hanging flyers in libraries and coffee shops changed when a new person became in charge of recruiting. Likely through cultural self-assessment, P10 understood that their use of social media as a recruiting practice did not align with some of their values. Despite acknowledging this misalignment in their practices and values, P10 could not change their social media recruiting practice to meet the needs of the families they aimed to serve.

> *"The spaces just got snapped up by the people who were fastest on social media. So if you have people who maybe, like work really long hours, or they're not on social media, or they don't have very good, like reliable internet access to get on and check things, like they're just going to be slower. They might miss the boat."* (P10)

P10's statements highlight the tension between implementing recruitment practices that may be more successful at filling enrollment and implementing recruiting practices that may serve students from the populations they hope to serve. Some for-profit informal CS learning programs faced this tension because they needed to fill enrollment in order to make a profit. With this tension in mind, P10's social media recruiting practice demonstrated cultural incapacity because of the likely bias it had toward families with more knowledge about their social media postings and more time to spend on social media. Contacting schools was another common recruiting practice used by informal CS learning programs and one that prior literature has reported as being common in the informal learning program space [46]. This recruiting practice can also demonstrate cultural incapacity. P6 reported recruiting from a few mid-to-high-income schools. P6's contacting schools recruiting practice demonstrated cultural incapacity because it only extended to locations where they could *"picture parents may be signing up that could get their kids to the program"* (P6). Parents who can spend the time to provide transportation to and from extra-curricular activities typically have a higher SES [57]. While we interpret P3 as conflating *"intent"* (P3) with *"financial means"* (P3), we interpret P6 as conflating income with the ability to *"get their kids to the program"* (P6).

P7 explained that it can be a lot of work to contact schools. Therefore, some programs, like P7, reported using third-party vendors like PeachJar as a way to reach out to schools. PeachJar worked as an intermediary between nonprofit organizations and schools allowing informal CS learning programs to save time. While PeachJar made contacting schools easier, it was not flawless. P7 noted that they had the goal of reaching students from *"underrepresented groups"* (P7) in CS, but they were not sure how to. While they had the desire to better serve students from HUGs in computing, they picked the path of least resistance and recruited from *"Schools that are in less rural settings [and] schools that have accelerated programs [because they] have, like have, many more chances to have students quite interested in what you offer."* Even though P7 had the desire to better serve students from HUGs, which would demonstrate a value for diversity if they had tried to follow through on their desire, they conflated student interest with students who attend schools with accelerated programs. P7 seemed to assume that schools with accelerated programs are more likely to have students who are interested in informal CS learning programs and prior research has suggested that may not be the case [54, 77].

Similar to P10's implementation of social media as a recruiting practice and P6's implementation of contacting schools as a recruiting practice, the purpose of P7's contacting the school's recruiting practice seemed to be to fill enrollment. Additionally, all three participants' reasons for implementing a recruiting practice the way they did were based on a conflation of students' interests or access with financial background.

How these programs implemented hosting programs at universities, social media, and contacting schools seemed to demonstrate some of the traits of cultural incapacity. More specifically, their recruiting practices seemed to continue to provide access to computing to people who already have access to computing and they made assumptions about how the financial backgrounds of students influenced their interest in computing.

5.2 Cultural Blindness

A few of the informal CS learning programs implemented some of their recruiting practices in ways that seemed to demonstrate cultural blindness. These programs demonstrated a belief that the implementation of their recruiting practices was equitable. Additionally, they often had goals of reaching students from HUGs, but either had no follow-through on their goal or would attribute failure to engage students from HUGs in computing to students' disinterest. Programs with recruiting practices at this stage seemed to believe they are unbiased, encouraged assimilation to the dominant culture, or ignored cultural strengths [21].

5.2.1 Students Aren't Interested. Our analysis revealed that most of the informal CS programs had the goal of serving students from HUGs in computing. However, when we asked about why they felt they were not getting good engagement from students from HUGs they sometimes blamed it on students' disinterest in computing rather than engaging in cultural self-assessment. For example, P4 reported that they reached out and contacted most of the schools in the region through the use of their mailing list. They explained that they had contacted schools that were diverse in respect to "*racial/ethnic status*" (P4). However, they still struggled to recruit students from these schools. As P4 stated, "*[It is] possible that potential participants from these groups do not hear about the program; teachers/parents don't think it is appropriate for them.*" When P4 offered potential reasons for why they were having a hard time recruiting racially and economically diverse students, they demonstrated cultural blindness by attributing their recruiting struggles to students from HUGs parents and teachers instead of evaluating their contacting school's recruiting practice.

Some programs' implementation of recruiting through social media demonstrated cultural blindness. For example, P11's social media recruitment practice demonstrated cultural blindness as their social media seemed to offer equal opportunity, but did not seem to acknowledge or address inequities. Their implementation likely led to biases against students from HUGs in CS. P11 reported that Facebook was the only social media platform that their program used. P11's goal with Facebook ads was more than just advertising their summer camps and after-school classes. P11 also wanted to host free online classes, *"Every Monday from 3 to 5pm we're doing lessons for kids. Anybody can join, we do live on Facebook Live... we invite everybody to join and actually do you know, free classes."* The free classes they hosted through Facebook Live likely could broaden participation in computing.

However, despite the follow-through on the free classes they offered, similar to other programs' social media recruitment practices, P11 utilized Facebook as a way to fill up class slots. While this demonstrates similar aspects of cultural incapacity similar to P10's social media practice, P11's social media practice differs from P10's because P11 appeared to believe that their social media practice seemed to create equity when it was creating equality. By providing free classes through Facebook Live, anyone *could* take the class, but P11 appeared to not recognize that some of the potential students they were trying to serve might have different circumstances and different access to resources. Instead, P11 suggested *"It comes down to who it's been sold to right? It's more of like who has been attracted to it because it's a free market."* While the free market does influence who participates in informal CS learning programs [28, 30], as the organizer of a program P11 likely had some ability to shape who CS is being sold to and who might be attracted to it through their recruiting practices.

P11 also appeared to demonstrate aspects of cultural blindness by not demonstrating a value for diversity and blamed the lack of engagement on students' not being *"attracted"* (P11) to computing. P11 stated, *"For example, for me as a businessman I don't care who I'm selling to. The more people I get, the better it is for the business. The more customers we get the better it is for the business. It doesn't matter where the customers are coming from."* While P11 suggests that their recruiting practice was equitable since anyone could join their free online courses, P11 also seemed to demonstrate a fundamental aspect of cultural blindness. That is P11 does not care about where students come from and we interpret P11 as suggesting that a person's culture does not make a difference in the opportunities they might have.

5.2.2 Encouraging Assimilation to CS Culture. Two aspects of cultural blindness include encouraging assimilation to the dominant culture and ignoring cultural strengths [21]. Some of the reasons and explanations informal CS learning programs had about their girls-only classes pointed to cultural blindness. For example, P11's implementation of girls-only classes seemed to demonstrate cultural blindness even though they partnered with Girls Who Code. P11 explained that they wanted everyone who came through their doors to learn CS if they truly wanted to, while also explaining how CS is an unbiased field. They demonstrated two conflicting ideas that seemed to influence how they followed through on this recruiting practice:

> *"I try to encourage everyone, we do everything we can to make sure that anybody who comes in, who comes in through our doors, or tries to learn from [program name] they have an actual opportunity to fully explore and understand whether this is something that they like or not like. Is it something that they want to do? And computer science doesn't care about age. It doesn't care about gender. It doesn't care about race. It doesn't care about anything, it cares only about skill and the ability to think logically."*

One aspect of cultural blindness is that programs at this point typically believe they are unbiased, encourage assimilation to the dominant culture, and ignore cultural strengths [21]. P11 seemed to encourage assimilation and ignore cultural strength by believing that CS is a meritocracy. P11 seemed to believe that by offering girls-only classes they are unbiased because from P11's perspective, girls-only classes may have meant that they were doing everything they can to reach girls. *"We do everything we can to make sure that anybody who comes in, who comes in through our doors or tries to learn from [program name]"* (P11). However, at the same time they seemed to blame students for not being interested in CS rather than acknowledging how curriculum and environment play a role in students' interest: *"But then it's up to the person what they're going to do with that"* (P11).

5.3 Cultural Pre-Competence

Many informal CS learning programs implemented their recruiting practices in ways that demonstrated cultural pre-competence. Oftentimes, these recruiting practices were changed due to organizers' realization that their old recruiting practices did not meet their BPC goals. When this occurred, program organizers' seemed to demonstrate a few of the elements of cultural competence [21]. Some of the more common elements that were demonstrated included a value for diversity, cultural self-assessment, and adaptations to diversity. However, a pitfall that kept programs' recruiting practices in the cultural pre-competence stage was when they did not track how changes they made could have influenced their recruiting efforts [21].

5.3.1 Passive Recruiting Practices Designed to Serve Students from HUGs. Some informal CS learning programs implemented passive recruiting practices, like social media, flyers, and mailing lists in ways that demonstrated cultural pre-competence. One of the participants described recruiting practices that required potential participants to seek out informal CS learning programs as passive. Below, we give examples of how informal CS learning program organizations implemented social media and mailing lists in ways that were culturally pre-competent. For example, P12's website showed that they used Facebook, Instagram, YouTube, Pinterest, and Twitter to inform people about their programs. All of their social media accounts had videos and posts on how they create inclusive classrooms and work spaces, the girls-only coding courses they offered, and the different kinds of scholarship opportunities they offered for girls and students from low-SES.

> *"Our scholarship programs have provided tens of thousands of educational experiences to underserved students to attend [Program name] programs. Through our Tuition Assistance Program,*

Corporate sponsorships, [Program name] has introduced students throughout the world to STEM, sparking their curiosity in tech. Every child deserves access to quality tech education, regardless of socioeconomic background. Our goal is to help bridge the digital divide." (P12 website)

Part of P12's goal was to broaden participation in computing, and the social media accounts that they used to recruit students reflected that goal. Their social media recruiting practice seemed to demonstrate cultural pre-competence because they showed their value for diversity and cultural self-assessment by reflecting on the information they thought was important to the populations they were trying to serve by displaying possibly helpful information on all their social media sites.

P12, P13, and P14 demonstrated cultural self-assessment; they seemed to realize that their social media recruiting practices may have not been aligned with their BPC goals. They showcased adapting to diversity by changing how they thought about social media in relation to the communities they were trying to serve and made changes to their social media recruiting practices based on their new ways of thinking. In describing the problems they faced in using social media to recruit, P14 noted that they had to change the way they used social media if they wanted to recruit students from the communities they were trying to serve.

"Nowadays, what we've been finding is most students don't... even have a Twitter account... they don't really check their Facebook... what we've been doing on social media has been around cultivating experiences that they want to share with their friends... events that are a break from coding that look really fun and are the sort of things you want to take a snapshot and send it to your friends." (P14)

The way P14 adapted their social media recruiting was intentional and based on the observations they made about the students they were trying to serve. By reflecting on the new ways their students used social media, P14 seemed to have their students share their experiences they had at camp with their friends. This adjustment was likely powerful because P14 shared that many of their students are from HUGs in computing and by having their students share their experiences with their friends, those students could have been showing other students from HUGs in computing that people like them can do computing.

Another passive recruiting practice that informal CS learning program organizers used was mailing lists. Their implementation sometimes demonstrated the institutionalization of cultural knowledge and adaptation to diversity. Some of these programs adapted their usage of mailing lists while others curated who was on their list. P5 and P14 used their mailing list to create a community of people they could ask to help recruit students. This use of mailing lists to recruit students is similar to using partners to recruit students. For example, P5 reported that they had built up a list of over 600 Deaf community programs. P5's approach to mailing lists was likely culturally pre-competent since they illustrated that they were maintaining and developing a network of hundreds of deaf and hard-of-hearing community organizations across the United States. While the design of their program focused on deaf and hard-of-hearing students which influenced their value of diversity, they also demonstrated institutionalization of cultural knowledge through their list of community programs. Their mailing list likely gave them more knowledge about and connections to the Deaf and hard-of-hearing community.

Instead of using their mailing list to contact previous customers, P14's reason for using their mailing list was to contact teachers, instead of students who had already attended their program because *"Repeat is not a huge focus of ours."* This implementation helped P14 achieve their goal of recruiting students from HUGs in CS and students who are not generally interested in CS:

Since P14's program did not focus on repeat, they could hone their mailing list to only focus on teachers. P14's use of their mailing list was culturally pre-competent because they created a mailing list of teachers who would potentially be able to help recruit new students year to year. Through this list, P14 demonstrated a value for diversity, the institutionalization of cultural knowledge, and adaptations to diversity.

When informal CS learning program organizers' shifted the focus of their mailing lists from trying to recruit students, to building a network of people that likely understands the needs and wants of the students organizers are trying to recruit, these organizers likely had a better understanding of the communities they were trying to serve. This shift likely helped them recruit students they were aiming to serve by giving them better insights into the unique experiences their potential students have.

5.3.2 Moving Away from Passive Recruiting. While some informal CS learning programs implemented passive recruiting practices, others started to move away from using them because they seemed to think that they did not help them serve students from the communities they aimed to serve. Program organizers that moved away from relying on mailing lists seemed to focus more on contacting schools directly or partnering with businesses to help contact schools. Below, we give examples of how informal CS learning program organizations implemented contacting schools and using partners to help recruit students in ways that were culturally pre-competent.

P13 reported that mailing lists were not very effective in recruiting the students they were trying to recruit, when compared to when they were focused on recruiting girls. P13 demonstrated cultural self-assessment when they explained that the reason they thought email lists were not effective was that they were too "passive," for recruiting students from HUGs in computing. Then, they showed an adaptation to diversity by starting to rely less on recruiting practices that were self-subscribed and instead focused on reaching specific schools that had a large proportion of students from HUGs in computing. For example, one of P13's goals was to reach out to schools that were primarily low-income and also had some sort of CS class. P13's contacting schools recruitment practice was culturally pre-competent since they followed through on their goal by piloting their new contacting schools' recruitment practice with three different schools:

> *"[We] identified schools that had large amounts of underrepresented minority students as far as CS is concerned. Then, also students that have more low income, but we also are looking for schools that do have some kind of nascent CS program as well... we've found that it's hard for us to do much with a school that, like, doesn't have any CS program."* (P13)

Along with demonstrating a value of diversity, P13 also demonstrated cultural self-assessment and adaptations to diversity. They had changed their focus from recruiting more girls to CS to recruiting students from HUGs. Based on this change, they assessed their recruiting practices and started to contact schools, which was something they had not done before. Then, they pilot their new contacting schools' recruiting practice to see if it would reach the students they were focused on recruiting.

Most informal CS learning programs that implemented contacting schools did so in culturally pre-competent ways because they demonstrated a value of diversity and cultural self-assessment or adaptations to diversity. For example, P14's program demonstrated a value for diversity and cultural self-assessment.

> *"There's a lot of public data on which schools are Title One, so receiving you know mostly free reduced lunch. And there's also a lot of public information just about the demographics of different schools... One of the big things that we've been doing since the beginning, has been to reach out to creative teachers. So that would be art, music, and acting. We've recently started expanding with literature... [we ask them] do you have any students that you think might want to make a*

> *soundtrack for a video game? Do you have any students who might want to write like the story for a video game?"* (P14)

P14 demonstrated cultural pre-competence because they reflected on their contacting schools recruiting practice to determine whether they were utilizing this recruiting practice to the fullest extent to meet their goals. By expanding which teachers they contact, they demonstrated an adaptation to diversity along with a value of diversity.

P1's goal was to provide a CS curriculum to students who might not have the opportunity to explore CS. One way they tried to achieve their goal was by contacting **Parent-Teacher Associations (PTA)** or extracurricular coordinators. Their goal demonstrated the value of diversity and influenced which schools they reached out to and who they reached out to. P1's reasons for who they contacted at each school were based on who would pay for their program:

> *"Each school, um, has some sort of a coordinator, the coordinator could be a teacher... And then in some schools... they just place that with their parent organization. Um, so I would have a contact for every school or every partner that we work with... Some schools have a very high percentage of free and reduced lunch. They have, you know, students who are a little bit more, um, marginalized. And so in their case, the students and parents don't pay, the school does... because they have those challenges, we built in a discounted rate for them... other schools... run their enrichment programming through their PTA or PTO, their parent organization, and so they pass along the cost right to the parents."* (P1)

P1 displayed cultural pre-competence because they demonstrated adaptation to diversity by changing who they expect to pay for their program based on which schools they contacted. Then, they seemed to demonstrate an understanding of the dynamic of differences by contacting PTA or **Parent Teacher Organization (PTO)**. By contacting these parent-run organizations they were likely more able to contact parents directly instead of relying on students to inform their parents. This demonstrated an understanding of the dynamic of differences because it is unlikely that all students will relay informal learning program information to their parents.

P5's informal CS learning program had the goal of increasing participation in CS among people who are deaf and hard of hearing. P5 demonstrated cultural knowledge of people who are deaf and hard of hearing by contacting schools beyond ones that are specifically designed for deaf and hard-of-hearing students.

Another way informal CS learning programs moved away from passive recruiting practices was by using partners as a way to recruit students. Partners were any business or non-profit that supported an informal CS program by funding their various supplies, and scholarship opportunities, telling students and parents about the program, or contacting schools. We only observed programs that use partners in culturally pre-competent ways.

For example, P1's reason for partnering with the local Parks and Recreation center was to provide free classes to students who attended predominantly low-income elementary and middle schools. The local Parks and Recreation center offered P1 the ability to better serve the students they were trying to reach which demonstrated adaptation to diversity. Similarly, P2 demonstrated adaptation toward diversity by partnering with Amazon in order to get around financial barriers for students because Amazon provided funding to students who could normally not afford to attend P2's program. Then, P14 demonstrated an understanding of the dynamics of differences by utilizing Girls Who Code's reputation of increasing representation of girls in CS to likely better attract girls to their program. Similar to P1, P10's reasons for partnering with a local Makerspace was that the Makerspace gave P10's program a space to host their program, hardware for the students to use, access to their mailing list, and social media accounts all for free:

"[They provide] the space, but then they also provide all the workstations. So they put together a bunch of like raspberry pi workstations and got monitors. And they also support [us] with, like, snacks and we do, like, registration through their registration. So they offer a lot of support in addition to just the space." (P10)

These informal CS learning programs that recruited students through their partners did so in ways that were cultural pre-competence because they not only demonstrated an adaptation to diversity but oftentimes also institutionalization of cultural knowledge. These programs demonstrated an adaptation to diversity by receiving support from their partners. Whether that support is in the form of providing space within a community to better reach students different programs may be trying to recruit, financial support to better fund students who may not be able to afford the program, or attaching the partner's name to the informal learning program to potentially better attract students. Then, they demonstrated institutionalization of cultural knowledge since their partnerships likely gave them a lasting relationship with students from communities they were trying to better serve.

P12 valued their partnerships more than most informal CS learning programs. P12 originally went with a bottom-up approach when contacting schools, but began to rely on their partners to reach out to schools on their behalf as a way to maximize their recruitment of students from HUGs in CS. In P12's case, relying on their partnerships was helpful because they partnered with programs like the National Coalition of Black Women, which likely allowed them to reach Black women better:

"[We contacted] counselors, the robotics team and like... do you know a student who would qualify? It was literally grassroots and so that's not scalable. We gotta paint with a broader brush... How do you do that? It goes back to the partnerships... There are the one offs where I go connect with schools, but more often than not it's the partnerships."

P12 suggested that they relied heavily on their partnerships and went as far as asking their partners if they had a specific population they were trying to reach so that they could personalize their course to their partner's request. They designed their programs off of what their partner wanted, "*it depends on the partner*" (P12), "*it's all contingent upon the partnership*" (P12). P12 provided an example where *"Nokia really wants to get girls involved. One of their criteria was that the girls have had exposure to tech before and they were interested in the tech field"*. P12's commitment to their partnerships likely gave P12 a better understanding of the needs of the students they were trying to recruit. Their commitment to partnerships also possibly offered their students chances to build their social capital through the brokering opportunities that hosting informal learning programs through technology companies can provide [17].

5.3.3 Reducing Barriers to Access. Informal learning programs can offer students the ability to learn new topics at a low cost. However, our analysis revealed that some informal CS learning programs are relatively expensive and some require that students bring their own hardware. Some informal CS learning program organizers recognized that the cost of attendance was likely too high for some of the families they were trying to serve and as such, they implemented recruiting practices focused on reducing barriers to access. The recruiting practices include advertising that they provide and offer need-based scholarships and hardware for students. Most programs used need-based scholarships in culturally pre-competent ways. One way that informal CS learning program organizers funded their scholarship programs was through their partnerships with businesses. P2 informed us that they thought offering need-based scholarships was important because one of the problems informal CS learning programs face in broadening participation in computing is the, "*Affordability of our programs.*" As such, P2 *"Partnered with Amazon to offer scholarships to underserved students who typically would not be able to afford to participate in our programs."*

Similar to P2, one of the ways P12 provided need-based scholarships was through their partnerships with businesses. In describing why they provided scholarships in this way, P12 spoke about barriers they faced in getting students to participate in their program:

> *"[Microsoft] opened their doors to these scholarship students and they... were targeting high school age Latinas and low income. And that day came and they had all these Microsoft executives who were gonna talk to them. [They] had LinkedIn there to set up their accounts, and an entire day of festivities, and they had 30 girls who said they were going to attend, and only two showed up."* (P12)

Access is only part of the problem around BPC. As a way to increase participation in their scholarship programs, P12 decided to focus on individual locations within the community to raise awareness about the scholarships. They started to reach out to local schools, organizations like the Boys and Girls Clubs, and YMCA to try and start increasing participation in their scholarship programs. P12's implementation of need-based scholarships was culturally pre-competent since it demonstrated a value for diversity, cultural self-assessment, and adaptations to diversity. They demonstrated cultural self-assessment and adaptations to diversity by implementing their practice specifically in the community to raise awareness about their scholarship programs because just offering the scholarship program was not enough.

However, not all informal CS learning programs can partner with businesses to provide scholarships or hardware. Some programs, like P6, P7, 11, and P13 required students or their parents to show proof of their low-SES. The reason these programs required students who applied for financial aid to show that they qualified for free and reduced lunch, was on food stamps, or some other Department of Human Services service was because they did not have a large amount of financial aid they could provide. P6 explained that students qualify for the financial aid if they *"Meet the free and reduced lunch criteria."* However, P6 went onto explain that *"It's a small fund, and as soon as the funds are exhausted, then we're then we're done for the year."*

P3's implementation of need-based scholarships was very similar to other informal CS learning programs' implementation. However, P3 required that students show some level of academic merit alongside proof of aid stating that they were *"Looking for people who are in a certain financial spot, and then, also there's some merit."*

P9 had decided not to run any summer camps or after-school programs due to COVID-19. However, they still informed us of how they used need-based scholarships: *"By working with K-12 Grants [Upward Bound and GEAR UP] we can provide camp experiences for students of poverty and minority students that would otherwise be unable to attend."* P9 explained that as they used more of the grant money, it became harder to renew their grants, forcing them to reduce the number of scholarships they could give. This put them in a similar situation as some of the other informal CS learning programs that did not have a lot of money to use for need-based scholarships:

> *"Not all districts or other service institutions have the time or ability to write grants, and even those that do, often may not meet some of the requirements for qualifying... leaving them unable to provide the service for their population that most need these supports. The original goal of our camps was to try to meet some of those needs, but as time passed and the grants that were originally used to fund the camps went away... and that meant having to charge tuition... for the very students we were hoping to target."* (P9)

There were a few ways that informal CS learning programs were able to offer need-based scholarships to students. Programs that operated within their financial means may have not been able to support as many students as programs that partnered with other organizations, but they still offered need-based scholarships as a way to recruit students in a culturally pre-competent way since they tended to demonstrate a value for diversity and adaptations to diversity. These programs made adaptations to their recruiting practices to offer some sort of financial aid to better support students.

Several programs provided hardware to help recruit students, all demonstrating cultural pre-competence. For example, P1 and 14 explained some of the locations they hosted their programs did not have computer labs. P1 explained, *"[We] have schools that don't have any laptops available for the students and we actually had to provide them. So we keep, um, 30 or so laptops on hand and we would kind of round Robin them, um, with different classes."*

Similarly, P14 stated:

> *"We had somewhere around like 200 laptops in various cities that were for that program where they can keep a laptop. If they participate, and so, you know, we also had, the, the managers. The, like, local volunteer people who are in charge of those, sort of find ways to distribute those to the students that would be needed as well so that they could participate."* (P14)

P14's implementation of providing hardware was different than P1's because P14 allowed their students to keep or build their own computers as a way to increase student interest in computing:

> *"We're typically going to follow up more with the student schools that are underrepresented and offer them more opportunities, like being able to reimburse the travel for students. We offer a thing where a bunch of donors fund laptops to give away. So if you build the game, you get to keep a laptop at the end of it."* (P14)

While not all informal CS learning programs could afford to give laptops away, providing hardware can be essential to make sure that a program is accessible. Both P1 and P14's providing hardware recruitment practice was culturally pre-competent since it demonstrated cultural self-assessment by reflecting on how their practices aligned with their goals. Also, their BPC-related goals seemed to play a role in why they both provided access to laptops.

Similar to P14, P12 was another program that could afford to gift computers and they explained that it was a new practice that they started to deploy during COVID-19:

> *"[We] had a program through SalesForce where we had 200 students come on through scholarship, and half of those students did not have computers, and so we ended up sending them a laptop. A really nice gaming laptop, which is what they would've been using [at program name] on campus. Not only being able to use it during the program but, upon successful completion of the program they got to keep it."* (P12)

Since not all programs could afford to give hardware to their students. One of the more common implementations of providing hardware as a recruiting practice was to have a computer lab on site. Both P1 and P13 had access to computer labs.

> *"The great benefits of working for the [University] is not only that we have access to all the labs, but we have our own computer labs as part of the CS program, of course. So we have several undergraduate computer labs... So we actually have a ton of lab space to bring people into. But the problem is getting them to campus in the first place if they don't have access."* (P13)

5.3.4 Aiming to Increase Students' Sense of Belonging. Some of the reasons informal CS learning programs had for implementing specific recruiting practices like hosting programs on college campuses and providing girl-only classes focused on increasing students from HUGs in computing sense of belonging. For example, some program organizers reported hosting their programs on college campuses because they wanted to show the students they were aiming to serve that they do belong on college campuses. Then, others who provided girls-only classes reported doing so with the aim of showing the girls who participated that they belong in CS.

Informal CS learning programs that used college campuses to recruit students in culturally pre-competent ways did so by creating brokering opportunities for students from HUGs in computing to access connections and opportunities. For example, P5's program goals included exposing older Deaf and hard-of-hearing students to CS to try and motivate them to pursue CS in college. They achieved one of their goals in part by hosting their program on a college campus:

> *"It was, it was put on by [College Name] and it was a Python-based course, and it had, it was, it was a pretty good online course, and the very first day we went in mass up to [College Name] in our van. And the teacher, you know, explained the course and the ASL interpreter was there. And then, and then, for the rest of the course they just did it in our lab on the schedule of that class. So they had to turn in their assignments on time and all that, but there was quite a bit of tutoring, and we had some, some, students who were tutors that work with us, to, to sit side by side with the students and explain things that they needed."* (P5)

P5 demonstrated a value for diversity by showing a belief that deaf and hard-hearing students could be successful computer scientists, *"[The] main goal was to sort of encourage and also keep two things, encourage people to pursue CS."* Then, they demonstrated cultural self-assessment with this recruiting practice by aligning their informal CS learning program that took place on a college campus with their goals and beliefs. Lastly, they demonstrated an understanding of the dynamics of differences by making sure the material was accessible. Not all deaf and hard of hearing people know ASL therefore, they made sure to also provide capture lists for students.

P13 had a similar goal with a different population, but P13 were struggling:

> *"Our ultimate goal is to also get them to campus at some point in the future. So saying, hey, we can do a lot with you in your classroom, but why don't you come up to us this time and we can show you around. So it's generating that interest and then that's when we kind of say okay well now imagine yourself here."* (P13)

Even though P13's program initially took place on a college campus, they had planned to host multiple programs in different places. That way they could overcome the transportation barrier the students they were trying to serve faced:

> *"The idea being that we would maybe hold one in each location simultaneously. Then, on the last day the [community center] group and the on-campus group meetup for, like, a tour, and a lunch or something. So that we're still getting them on campus and we're providing the transportation."* (P13)

P13's implementation of hosting their program on a college campus demonstrated a value for diversity, adaptation to diversity, and an understanding of the dynamics of differences. P13's recruiting practice of hosting their program on a college campus followed the recommendations made by [17]. Their plan is to host their program in two different locations and then bring all the students together for a day to possibly achieve their goal of getting students to imagine themselves attending college. This plan showed a value for diversity and an adaptation to diversity because they adapted their practice to mitigate the transportation challenges students faced. Then, P13 demonstrated an understanding of the dynamics of differences by understanding that: *"Representation is really, really important. For students to imagine themselves at [College] they have to literally see themselves and their community at the school."*

Most other programs had implemented a pre-competent practice of girls' only classes, aiming to increase the participation of girls in CS. These programs demonstrated a value for diversity by clearly stating that they were trying to *"close the gender gap"* and change some of the stereotypes around computing. For example, P10's website stated, *"[Our goal is] to close the gender gap in technology, and to change the image of what a programmer looks like and does."* (P10 Website). Similarly, P12 pointed out that, *"So again from the very early time of [Program name], we've had opportunities for girls specifically."*

Other programs followed through on their goal of increasing participation from girls in CS by changing the content of their girls-only classes:

> *"For our girls only programs, instead of doing, like, AI coding, they're going to do you know you know cool fashion design, that's going to be there. You know, stuff that they're gonna say, design like a tech fashion wearable thing. Yeah, creating programs for them and then carving out those spots and putting it through that's that's been our, our method"* (P3)

P3 girls-only recruiting practice demonstrated cultural pre-competence because they suggested that they attempted to improve recruiting girls by offering a class that was designed to entice girls to sign up. However, not all programs that implemented girls-only classes found it to be successful from an enrollment perspective. For example, P1, P3, and P14 struggled to fill classes:

> *"They would run all girl classes, um, led by a female instructor, um, a female assistant instructor. And, you know, there's all kinds of organizations that do that. A lot of schools actually have those programs in their schools. So we still, from time to time, we'll offer, um, an all girls class, but we don't seem to fill that."* (P1)

> *"We're working with Girls Who Code, for example, will give them 100 percent off coupon codes, and the reason for that is mostly just because what we were finding early on was that when we told everyone the event was free, people, obviously, like a lot of people would register and no-show, but one of the really interesting things that we noticed early on was that the people who are no-showing were more likely to be those beginners... maybe they're just waking up on Saturday, and they're saying like I'm not really going to fit in here I'm just not going to go to this."* (P14)

These programs demonstrated a value for diversity and cultural self-assessment by trying to make sure their girls-only classes would recruit girls. P1 made sure that their classes had female role models and P14 tried offering *"100% off coupon codes,"* but both programs still struggled to recruit girls. However, P14 implemented a solution to their problem that seemed to work. They had told students that their events cost money, but would liberally hand out promo codes that would reduce the cost significantly:

> *"By saying that it costs something, even though it, you know, even though the promo codes are given out pretty freely, and even though it's very easy to get a free ticket. We were finding that the no-show rate was a lot lower for beginners, somewhere between 10 to 20 percent versus like 50 to 60 percent, so that made a big difference."* (P14)

6 Limitations

Interpreting our results requires recognizing the limitations of our study design and data. For example, our research focused on the recruiting practices of informal CS learning programs used in the Northwestern United States. Informal CS learning programs elsewhere in the world may be using different recruiting practices, offering different incentives, and facing different problems. While we asked participants to inform us of the practices they used during and before the pandemic, it is possible that they did not inform us of everything they used to do since our study occurred during the COVID-19 pandemic. As such, our participants may have unintentionally shared more information about their current practices and not those that they previously used. Additionally, our sampling methods returned 36 programs with only 14 participating in our study and sharing their recruiting practices. That means that less than 40% of the informal CS learning programs that we contacted participated in our interviews. While the informal CS learning programs had substantial overlap in their set of recruiting practices, more such practices may exist and this may be better captured by interviewing staff working outside the Northwestern United States. Finally, the interviews we conducted were typically only 30 minutes and we were unable to get data from organizers about the impact of their practices on recruiting diversity. In addition to our short interviews, as noted earlier, we did not design our interview questions with the cultural competency framework in mind.

7 Discussion

In this section, we will start by discussing our findings for both research questions. Then, we will connect our findings to the literature surrounding recruiting practices. Lastly, we will propose recommendations for practitioners on how to implement recruiting practices based on our findings and the directions that future research should investigate.

With respect to our first research question, we find that informal CS learning programs report a wide variety of recruiting practices and tend to report having BPC goals. However, there was little variation in recruiting practices used: most programs relied on the same few practices such as social media advertising, mailing lists of parents of prior attendees, contacting teachers, or using flyers. With this in mind, the cultural competency of recruiting practices was influenced by nuances in their implementation rather than the variety of recruiting practices used.

For our second research question, we saw how informal CS learning programs used and implemented their recruiting practices varied greatly. Specifically, in the extent to which organizers relied on stereotypes about particular groups, made assumptions about particular groups' knowledge or interests, and the extent to which they examined their assumptions to improve their practices. Many participants showed no awareness that how they decide to implement their recruiting practices could impact BPC efforts. This lack of awareness combined with assumptions about students from HUGs is what hindered many programs achieving cultural pre-competence. However, when participants reported examining their assumptions, they also reported adjusting their recruiting practices to be more culturally competent. Note, that not all adjustments made to recruiting practices were due to reflection: some were due to resource limitations. This highlights how money, hardware, and time can and do shape the ways in which informal CS learning programs implement their recruiting practices. Oftentimes, resource limited programs valued diversity, but challenged to achieve their diversity goals likely resulting in implementing recruiting practices in ways that were culturally pre-competent or lower.

Continuing the discussion of our findings for the second research question, it was in the nuance of implementation of the same recruiting practice that differences in cultural competency emerged. For example, many programs contacted schools. However, few were intentional about contacting schools with a high representation of students who qualified for free or reduced-price lunches. This intentionality in how programs decided to implement their recruiting practices likely helped them achieve their BPC goals. However, overall most of the implementation of these recruiting practices were culturally pre-competent or worse.

We hypothesize that achieving cultural competency or proficiency requires a multi-step approach. Programs should start with cultural self-assessment, followed by intentionally implementing recruiting practices and institutionalizing knowledge about the communities they aim to serve.

This approach aims to better understand and adapt to the needs of the communities they aim to serve.

Our findings extend the body of literature around what recruiting practices informal CS learning programs use and how they design them. For example, prior research looked at how 59 STEM outreach programs recruited students and found that the most common these programs recruited students was by contacting schools [46]. Additional literature has documented this recruiting practice commonly used by informal CS learning programs [6, 20]. Our findings add insight into this recruiting practice by elucidating who informal CS learning programs contact when they contact schools. Our results suggest that there are multiple people informal CS learning programs can contact within the school and that who they contact may influence which students attend their program. For example, some of the participants we interviewed reported contacting math or CS teachers while other participants who reported more specific BPC goals contacted music, English, and art teachers.

Some prior research [1, 17] offer seemingly contrasting recommendations for how informal CS learning programs should decide on where to host their programs. For example, Akiva et al. [1] suggests that if informal CS learning programs want to recruit students from HUGs in computing they should consider hosting their programs in local communities rather than at colleges or museums because it is easier to engage students from HUGs in computing in their community rather than in a museum or on a college campus. At the time of the interviews, the informal CS programs we spoke with were hosting their programs online due to the COVID-19 pandemic. However, many participants spoke about where they used to host their programs. Some hosted their programs in local communities like Akiva et al. [1] suggests because they thought it would easier engage students from HUGs in computing. However, other programs were hosted on college campuses. Some participants who hosted their program on college campuses reported that college campuses could connect students to further CS opportunities. This reasoning aligns with Ching et al. [17] recommendations and contrasts with Akiva et al. [1]. Ching et al. [17] recommends bringing students from HUGs in computing to computing-related locations because these locations could connect students to further CS opportunities and empower them to continue to pursue CS. Our findings suggest that the cultural competency of deciding where to host the program is influenced by the reasons programs have for hosting their program in a specific location rather than the location itself. In other words, while the recommendations of prior research [1, 17] seem contrasting, they may not be because both implementations are based on the goal of BPC.

Our results suggest that there is some overlap between how informal CS learning programs and CS departments recruit students. For example, some of the recommendations for how CS departments should recruit students from HUGs in computing include working with high-school teachers, communicating with guidance counselors, using role models, offering multiple points of entry into the department, and making contact with the local community [20]. Some of these suggestions overlap with how our participants implemented their recruiting practices. For example, some of our participants reported contacting schools and specifically the guidance counselors. Our participants also added to this recommendation when reported the benefits they perceived to gain by contacting teachers along with or instead of guidance counselors.

There are some implementations of recruiting practices CS departments use that are less aligned with our participants' implementations. For example, some CS departments have their faculty and student ambassadors engage potential students and their guardians [81]. While it may be challenging for informal CS learning programs to implement this practice since they do not have faculty, they could have staff who likely have a CS background speak about their experiences in computing and how they became interested in the discipline. Additionally, some CS departments track the results of their recruiting practices to better understand how effective some recruiting practices are over others [81]. Only one of our participants reported tracking the effectiveness of their recruiting practices and changed their implementation based on the results.

7.1 Future Work

These results and limitations reinforce the idea that cultural competency is shaped by how informal CS learning programs implement their recruiting practices. Additionally, having BPC-related goals is not enough because our results and prior research suggest that it is the specific implementation of the practice, and following through to evaluate its impact is key to BPC [81]. However, these results also raise additional questions:

- How does the emphasis on different aspects of recruiting practices affect both the experiences of learners and their long-term involvement in the field of computing? For example, are partnerships with community organizations more or less effective than partnering with culturally competent teachers?
- How do parents and guardians experience the recruiting practices we reported? Prior work has narrowly considered the role of web search [29], but how do parents and guardians experience social media and mailing list "remarketing" efforts"?
- How might advocates improve the cultural competence of the recruiting practices used in informal CS learning programs, and how might those interventions ultimately broaden participation?

While evidence around recruiting in informal CS learning is still developing, the evidence we present here, along with more general research on cultural competence in education, does have implications for practice. It's quite clear for example that informal CS learning programs should (1) develop their cultural competence by examining their assumptions and values, (2) intentionally design and evaluate their recruiting practices, and in doing so, (3) pay close attention to the details of implementation. But it's also clear that the overall design of programs and curricula interact with recruiting: organizations should be mindful of equity gaps, identifying ways of offering hardware to rent, borrow, or keep; they should address transportation barriers; and they should follow the examples of some previous researchers [4, 24, 31] who designed culturally responsive curriculum with particular communities in mind to shape who is enticed by recruiting practices.

7.2 Conclusion

If informal CS learning programs can begin to follow these practices, guided by any further evidence from research, we can start to address inequities that exist in the implementations of different recruiting practices. And if we do that, perhaps all youth will have the opportunity to develop an interest in CS in ways that are culturally responsive and sustaining.

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