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# Uneven Playing Field: Examining Preparation for Technical Interviews in Computing and the Role of Cultural Experiences

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# Uneven Playing Field: Examining Preparation for Technical Interviews in Computing and the Role of Cultural Experiences

**Abstract**

While starting a career may be challenging in any field, in computing the process tends to be aggravated by requirements of digital portfolios and technical interviews that necessitate coding extemporaneously. During the programming components, candidates are expected to offer a solution, while also giving consideration to the choice of algorithm and its time complexity. Although intended to assess the competency of the job applicants, the process is often more akin to a professional examination. Applicants are encouraged to prepare months, or even years before they begin looking for a position, an expectation that neglects to consider the obligations and responsibilities students already have. Moreover, this presumption can result in an unequal divide between those who have the time to commit, and those who are unable to do so. To examine students' preparation for technical interviews and their own cultural experiences, we administered a survey at three metropolitan universities in Florida. Specifically, we utilized social cognitive career theory to examine: 1) Students' preparation practices for technical interviews; 2) The impact of cultural experiences on preparation time; and 3) The relationship between preparation and job attainment. To address these topics, we used descriptive statistics, Shapiro-Wilk tests, Wilcoxon rank-sum tests, and Kruskal-Wallis tests. We also applied the community cultural wealth model to interpret our results. We observed that, in our sample, White students began preparing earlier for technical interviews, spent more time preparing, and received more job offers than non-White students. Females also spent more hours preparing on average, and received more job offers than students that did not identify as female. However, female, Black/African American, and Hispanic/Latinx students were more likely to have cultural experiences that would impact their availability to prepare, including non-computing related jobs, caring for a family member, or ongoing health issues. While we do consider the support mechanisms students may leverage to overcome obstacles, in general, these results emphasize the larger issues in existing hiring structures, and demonstrate the importance of not treating students as a monolith. The findings from this work are intended to inform educators about how to better prepare students to succeed on technical interviews, and to encourage industry to reform the process to make it more equitable.

## 1 Introduction

Between 2019 and 2029, demand for workers in computing occupations are expected to surge 28.8% [1]. For specific positions the projected rate is even higher, with 35.0% for software developers/software quality assurance analysts and testers, and 43.7% for computer and information research scientists. Despite these growing needs, the computing industry struggles not only to find enough employees, but also to obtain equitable representation of Black men, Hispanic/Latino men, and of women from all racial/ethnic backgrounds [2–4].

Major technology companies like Google, Facebook, and Twitter admit that their diversity is not where it should be [3, 5]. Their workforce is 60% White, 30% Asian, and 6% or less are composed of Hispanic or Black workers [3]. At all three companies, women were only 30% of the total employees. Given the preponderance of White and Asian males in computing [3, 6], it is important to consider how workplace practices impact minoritized populations. One of the biggest challenges to engaging underrepresented groups in computing includes the hiring process itself [7].

While technology companies have created diversity programs/initiatives, and have worked to improve their recruitment and retention practices, e.g., expanding recruitment to Grace Hopper Conference and historically black colleges and universities (HBCUs), issues still remain [3, 7–10]. In an effort to make hiring practices more equitable, technology companies like Google, IBM, and Apple eliminated the barriers of grade point average (GPA) and/or possessing a college degree. Instead, they favored using a heightened focus on technical proficiency measured using programming or coding challenges [5]. Yet this shift has resulted in a new set of concerns, and structural inequalities. While it is common in hiring that each company has their own interviewing styles and expectations, technical interviews are a hurdle unique to computing fields, referring to computer science (CS), computer engineering (CE), and information technology (IT) [7, 11, 12].

As described in this work, **technical interviews** refer to a hiring interview for a computing position that occurs online, via phone/video call, or on-site/in-person, and that includes any combination of problem solving, coding, or programming tests for job candidates [11–13]. Preparation for the technical components of the hiring process is expected to begin months, and even years, before a student ever applies to a job [13]. These industry expectations are on top of students' normal coursework and personal/cultural commitments they already have, which results in an inherent inequity between those who have the time available and those who do not.

Many students work while in school (approximately 70%) [14]. However, low-income students (referring to those with family incomes that fall below 200 percent of the federal poverty line) are more likely than their peers to work longer hours and to hold full time employment [14]. Researchers have noted demographic disparities among working students, as low-income working learners are most often women, Black, and Latinx students. Furthermore, approximately one third are older students (above age 30) [15], who often are dealing with increased cultural responsibilities such as caring for children or other members of the family [14].

While there is a small subset of scholarly literature dedicated to examining the "leaky hiring pipeline" and what is expected during the hiring process in computing [11, 16], it is unknown how it affects students from different gender, racial, and ethnic backgrounds. It is also unclear exactly what kinds of external commitments computing students have, and how they prepare for technical interviews. To address this gap in the literature, we sought to answer the following specific research questions (RQs):

- **RQ1:** *How do students prepare for technical interviews?*

- **RQ2:** *How do differences in personal situations and cultural experiences impact preparation time for technical interviews?*
- **RQ3:** *How do differences in student preparation impact job attainment?*

We utilized Social Cognitive Career Theory (SCCT) as our main theory guiding this work, and also used the Community Cultural Wealth (CCW) model to analyze the results. SCCT has been used to describe how career choices are made [17–20], and is applied here to guide the complex relationships between personal inputs and the contextual influences that impact the technical interview preparation. Then we examined how the action of preparing impacts career goals and job attainment. **Cultural experiences** are defined as the knowledge learned and shared, for which activities, behaviors, and the interpretation of experiences define everyday life [21–23]. Specifically, we assessed caring for others, holding a job while in school (in a computing position or non-computing position), and social support (in terms of home environment and peers).

In the rest of this document, we will first review the background work in Section 2. Then, we will discuss the theoretical frameworks driving this research in Section 3. In Section 4, we detail the methods including the survey conducted, demographics of the population of study, and statistical analysis. Then we provide the results in Section 5, and a discussion of the findings in Section 6. In Section 7 we describe the limitations of our work, and we conclude in Section 8 with a summary and suggestions for future work in the field.

## 2 Related Research

During technical interviews, job candidates are often asked to solve problems by programming or coding on either a whiteboard, with paper and pencil, or via a text editor [11–13]. Throughout the process, they are encouraged to describe their thinking and are expected to consider the optimal performance of their solution, referred to as the time complexity. Although intended to assess programming capabilities, being expected to simultaneously present a solution while speaking through their thought process is not only challenging from the examination standpoint, but it can also be cognitively taxing [12]. Furthermore, such methods neglect the bias that may be inherent in this type of evaluation. For example, when considering gender differences in problem-solving, many tools are considered exclusionary for females [24]. Scholars have also noted that minoritized students may be even less likely to know how to prepare for technical interviews, and that fears of impostor syndrome may discourage them from going through the process [7].

Technical interview questions vary in complexity and scope. In order to be proficient at answering these questions, job applicants are not only expected to have a solid foundation in data structures and algorithms, but are also required to solve these problems quickly [25]. Applicants are encouraged to use preparatory books, mock interviews, tutorials, websites to teach or practice coding, and/or code katas (exercises that enables programming practice and development of coding abilities) to prepare [7, 13, 26–28]. While such recommendations can help to improve job candidates' problem solving accuracy and speed, they do necessitate a substantial time commitment. Furthermore, in addition to focusing on programming skills, preparation for the hiring process may also entail the cultivation of a digital portfolio, and/or completion of side-projects, coding competitions, and hackathons [13, 28].

Behroozi et al. (2019) previously examined perceptions of technical interviews based on anecdotes posted to Hacker News, an online community and forum discussing topics relevant to hackers and software practitioners [25], and through Glassdoor [11]. They found that although hiring managers claim the process is meritocratic, job candidates find them “subjective, arbitrary, unnecessarily stressful, non-inclusive –and at times– demeaning to their sense of self-worth and self-efficacy” [25]. Furthermore, candidates expressed concerns about the amount of time preparation required, and the inherent bias that may give those with more free time an advantage. Others commented that the types of questions asked, and knowledge of data structures expected to be known extemporaneously is not reflective of the tasks actually encountered in a computing position.

While these findings indeed revealed major concerns, the research did not consider the nuances that may arise from individual differences [11, 25]. On HackerRank, 95% of users were male, and there was no information about the race/ethnicity of participants [25]. Furthermore, reviews from Glassdoor also neglected to include demographic information, and the authors noted they may be subject to hyperbole effect in which candidates with extreme experiences are more inclined to post on such forums [11]. As such, to truly capture a broader understanding of hiring experiences across job applicants, more inclusive of those who identify with different gender, racial, and ethnic groups, further analysis is needed.

Previously, Hall and Gosha explored interview preparation as part of an examination of students’ performance on technical interviews, with participants from a Historically Black Institution [7]. Although the sample size was small ($n$ = 24), and limited to a single institution, they found that the students surveyed typically utilized mock interviews (58.3% of the time) to prepare for technical interviews. Only 12.5% of students did not prepare at all. They did not assess the gender of the participants. To reconfirm and expand upon these findings, we explore preparation methods and time spent, and then further evaluate the cultural experiences that may impose additional support benefits and constraints.

## 3 Theoretical Frameworks

In this work, we use SCCT and CCW as an interpretive lens for understanding the results of our survey. We further describe SCCT in Section 3.1 and CCW in Section 3.2.

### *3.1 Social Cognitive Career Theory*

**Social Cognitive Career Theory** is often used to understand the intrinsic and extrinsic variables that influence an individual’s career behaviors [17–20]. Derived from Bandura’s general social cognitive theory [29], self-efficacy, outcome expectations, and personal goals are central facets of the framework, and are considered foundational aspects for career development [19]. Applying a bidirectional causality model, personal attributes (including physical characteristics and affective states), actions, and external environment factors describe the influences that shape choices.

An overview of SCCT as it pertains to computing careers and preparation is shown in Figure 1, adapted from a combination of Lent et al. [17] and other STEM-specific researchers [30, 31]. Achieving mastery of skills (performance and accomplishment), social persuasion, experience with computing activities (e.g., programming) and topics, and emotions can impact computing self efficacy [32]. Positive computing experiences are key to developing an interest and career goals in computing. Ideally, both interest and self-efficacy in computing are developed. This leads to making a choice goal to begin a computing career, which drives preparation for technical

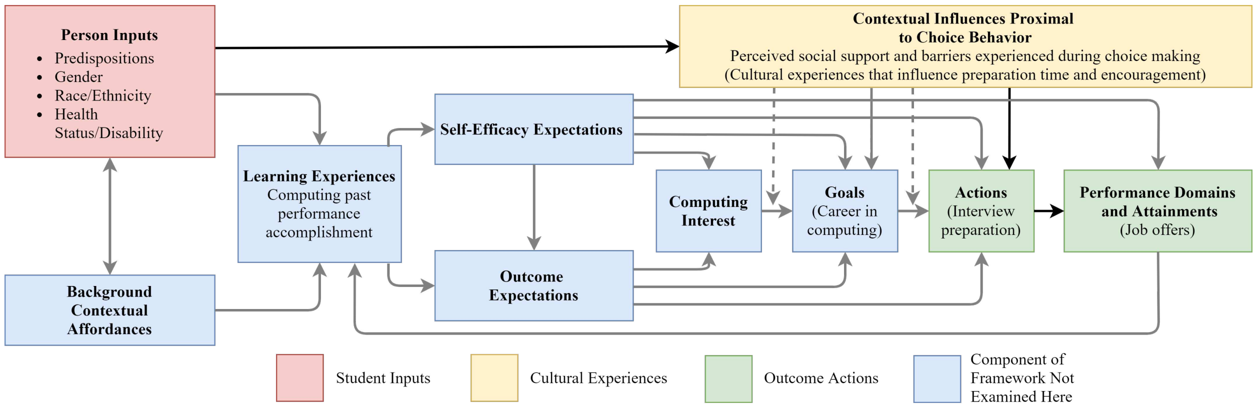


Figure 1: Overview of social cognitive career theory (SCCT) as it pertains to students seeking computing positions

interviews. Finally, these actions (of interview preparation) and self-efficacy expectations can influence performance in an interview, which impacts attainment, in the form of job offers.

In STEM fields, SCCT has been a key framework for investigating factors which contribute to an underrepresentation of women, Black/African American students, and Hispanic/Latinx students, in part due to its explicit consideration of gender, race, and ethnicity as "person inputs" [33]. Previously, the SCCT model has accounted for interests and persistence goals of students in computing [34]. In addition, it was demonstrated that supports and barriers lead to goals via direct paths, whereas there is an indirect link between contextual variables and goals mediated through self-efficacy. Social supports and barriers that students experience impact the goals of computing students regardless of whether they were from majority populations or minoritized groups in computing (women and African American students) [20]. As such, the model was considered to have cultural validity, and adequate fit across populations. However, the path leading from self-efficacy to outcome expectations was "somewhat larger" for female students. The authors posited that factors beyond self-efficacy may impact outcome expectations such as perceived notions about what careers in computing mean in regard to work-life balance.

We applied SCCT to explore how person inputs impact contextual influences proximal to choice behavior, to affect the actions of technical interview preparation, and ultimately job attainment in computing. While we do present descriptive statistics for all students to offer a broader look at students' technical interview quantity, preparation, and outcomes, we also consider how specific groups are impacted. We focus on the person inputs of gender, race, and ethnicity to compare the experiences of the computing majority, White and Asian students, against populations minoritized in computing, specifically women, Black/African American students, and Hispanic/Latinx students.

### *3.2 Community Cultural Wealth Model*

To better explain our findings, we also employed the **Community Cultural Wealth (CCW) model**, as shown in Figure 2. Developed by Yosso [35], the CCW model builds on critical race theory epistemologies and applies an anti-deficit approach [36] to describe how minoritized populations harness their own inherent capital to combat oppression. Previously, CCW has been demonstrated as an effective tool for considering the “[...] array of knowledge, skills, abilities and contacts possessed and utilized by Communities of Color” [35, p. 77].

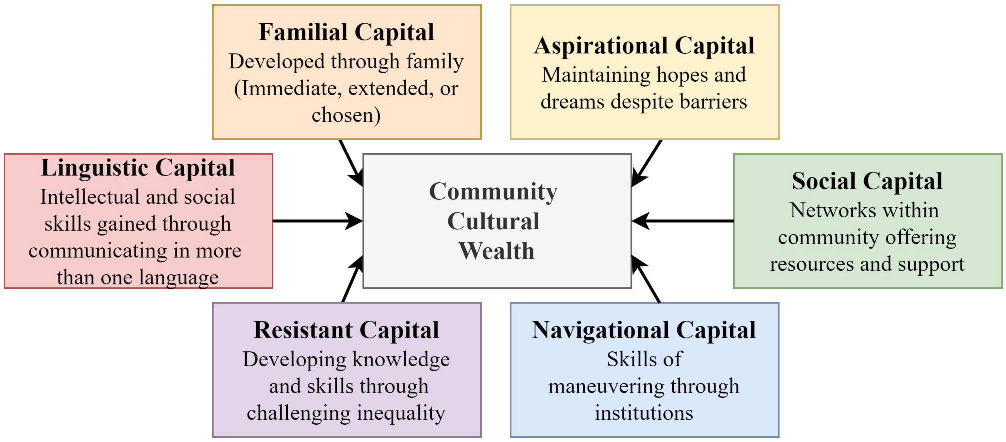


Figure 2: Overview of the community cultural wealth (CCW) model

Within the CCW framework, Yosso describes six interconnected forms of cultural capital as follows [35]:

- *Aspirational capital*: Sustaining hopes and dreams despite real and perceived barriers
- *Navigational capital*: Activating adaptive strengths and skills to maneuver through oppressive systems and social institutions (like universities, or the computing industry)
- *Resistant capital*: Developing knowledge and skills through behaviors challenging inequality
- *Linguistic capital*: Applying intellectual and social skills gained through communication in more than one language and/or style
- *Familial capital*: Utilizing forms of knowledge and support obtained through family (immediate, extended, or chosen)
- *Social capital*: Drawing on networks of people and resources from one’s community

Research in STEM fields has shown that CCW can be a powerful approach for student engagement, persistence, interest, and for skill development [37–41]. For example, peer support leverages aspirational capital and help minoritized populations “[...] to see themselves as STEM-engaged individuals and persist towards STEM careers” [39, p. 6]. Peer support can also tap into social capital, as students build a community and work together to study and to solve problems [41]. In this work, we considered how such ideas can extend to the contextual influences of SCCT that impact interview preparation, and we used CCW to interpret our findings.

## 4 Methods

To examine preparation for technical interviews, and commitments of individuals of different races, genders, and ethnicities, we conducted a survey of students’ practices and cultural experiences. In this section, we describe the methods employed. First, we present the survey on students' preparation and experiences in Section 4.1. Then we share the demographics for the population which completed the survey in Section 4.2. In Section 4.3, we discuss the data analysis.

### *4.1 Survey Development and Administration*

The survey instrument consisted of 46 questions in total, which included demographic information, questions about the students' academic status (e.g., year in college, major, and GPA), and inquiries into the students' interests and long-term goals. Additionally, questions were asked about students' experiences with technical interviews, and their cultural experiences (such as jobs they may hold, if they are caring for others, etc.). The questions used in our analysis, and corresponding response options, are given in the Appendix.

While the bulk of the questions were previously validated [42], additional questions were added pertaining to technical interviews by the project team. These new questions were developed based on prior literature, and were confirmed with feedback from key stakeholders, including students and professors, to establish face and content validity. A pilot study of the revised survey was conducted to further ensure reliability and validity. After the Institutional Review Board approved the protocol, the finalized survey was administered online to computing students at three large, metropolitan public universities in Florida in the Fall of 2020.

### *4.2 Demographics*

Responses were collected from computing students from CE, CS, and IT majors, to obtain a total sample of $n$ = 740. Information about the students' academic standing and their gender identity is presented in Table 1. Then we detail the racial/ethnic affiliations in Table 2.

| **Academic Standing (Year)** | | | | | **Gender Identity** | | |
|---|---|---|---|---|---|---|---|
| *1st* | *2nd* | *3rd* | *4th* | *Past 4th* | *Male* | *Female* | *Other** |
| 6.8% | 9.5% | 18.5% | 43.4% | 21.8% | 74.9% | 23.0% | 2.1% |

*Reported as transgender, agender, a gender not listed

Table 1: Academic standing and gender identity of participants

| **Racial/Ethnic Affiliation** | | | | | | | |
|---|---|---|---|---|---|---|---|
| *White* | *Black/ African American* | *Asian* | *Native Hawaiian/ Pacific Islander* | *American Indian/ Alaskan Native* | *Hispanic, Latinx, or Spanish origin* | *Middle Eastern/ North African* | *Another Race Not Listed* |
| 42.2% | 8.4% | 14.9% | 1.1% | 0.4% | 32.7% | 2.4% | 1.6% |

Table 2: Racial/ethnic identity of participants

Although demographics were collected using non-binary gender identities, and multiple racial/ethnic affiliations, we did limit the scope of our analysis to focus specifically on women, Hispanic/Latinx students, and Black/African American students. For the statistics that follow, we consider each underrepresented categorization as a self-identified label relative to those that did not self identify as such within the sample. For example, females were considered relative to males and students who identified transgender, agender, or a gender not listed. Also, for Black/African American students and Hispanic/Latinx students we explored each separately and looked at whether students reported identifying with those racial/ethnic groups or not.

*4.3 Data Analysis*

Data were cleaned and analyzed using **R** version 3.6.1 in **RStudio**, version 1.1.456. In all of the tests, we considered a $p$-value $< .05$ as significant [43, 44]. Initially, descriptive statistics were collected. For further analysis, Shapiro-Wilk tests were run to evaluate the normality of the data [45]. The observed $p$-values were significant, indicating a non-normal data distribution. Consequently, non-parametric tests were used to assess the impact of cultural experiences on interview preparation and job attainment for each group.

In particular, Wilcoxon rank-sum tests (equivalent to a Mann-Whitney U test) were utilized to compare values from two groups in the population, and to determine if there were significant differences [44]. We also used Kruskal-Wallis tests, which are similar to the Wilcoxon rank-sum tests but are for more than two groups [44], to examine the link between cultural experiences and preparation. Freeman's theta ($\theta$) and epsilon-squared ($\epsilon^2$) statistics were calculated to determine the effect size of statistically significant differences in how early preparation began, and the hours spent preparing [43, 44]. For effect sizes, we considered a small effect for $\epsilon^2$ to range between .01 and $< .08$, a medium effect to range between .08 and $< .26$, and a large effect to be $\geq$ to .26 [44]. For Freeman's $\theta$, we considered a small effect for to range between .05 and $< .20$, a medium effect to range between .20 and $< .38$, and a large effect to be $\geq$ to .38.

## 5 Results

In this section we discuss the findings pertaining to students' preparation, and the contextual influences that are proximal to choice behavior and which may provide supports and barriers. In addition, we provide evidence for the link between preparation and job attainment. For framing, we first describe how many technical interviews students in the population report having (Table 3). Although 48.0% of students did not report having any technical interviews, more than half of students reported completing an interview.

| **Number of Technical Interviews** | | | | | |
|---|---|---|---|---|---|
| *0* | *1-2* | *3-4* | *5-6* | *7-8* | *9 or more* |
| 48.0% | 29.7% | 13.5% | 4.2% | 1.2% | 3.4% |

Table 3: Number of technical interviews students report, as percent of total students

*5.1 RQ1: How do students prepare for technical interviews?*

To explore students' preparation practices, we first examined the resources students report using to prepare for technical interviews, described in Section 5.1.1. In Section 5.1.2 we considered the amount of time devoted to preparation. Then we consider the differences in preparation time between students of different gender, racial, and ethnic groups in Section 5.1.3.

### 5.1.1 Resources Utilized for Preparation

To better understand how students prepared for their technical interviews, we asked students who had completed at least one technical interview what resource(s) they used. As shown in Figure 3, most often students utilized online coding resources (e.g., LeetCode or HackerRank). Students also prepared by reviewing course notes or assignments, and participating in mock interviews. It should be noted that since students could select more than one resource, percentages indicated are relative to the total students (e.g., 13% worked on projects outside of school or work, and 87% did not report doing so). Overall, only 9% of respondents chose "no preparation," meaning that the majority of computing students who had interviews did utilize some form of preparation (either in singularity or applying a combination of methods).

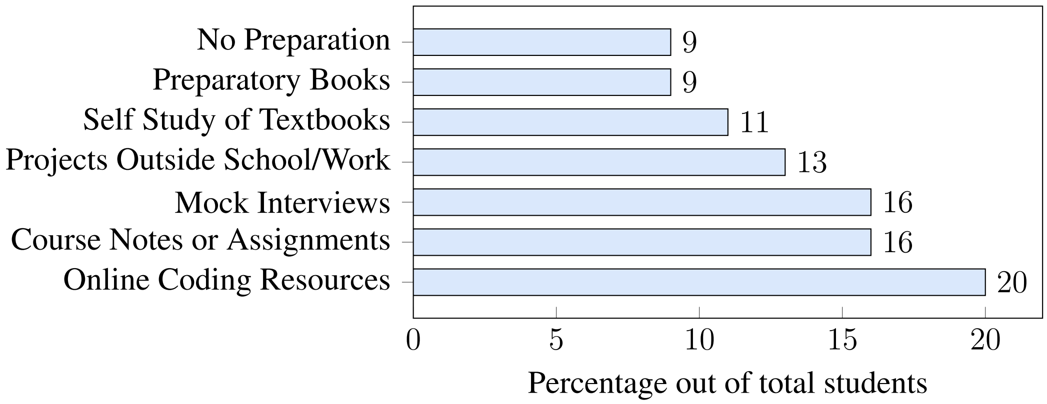


Figure 3: Resources utilized for technical interview preparation

#### 5.1.2 Time Spent Preparing

We also examined how early (or far in advance) preparation began, and how long (in terms of hours spent) they prepared. The results for all students are illustrated in Figure 4. As shown, the majority of students began preparing for technical interview(s) 1 week or less (47%), or 2 weeks to 1 month (42%) beforehand. Students typically spent 1-5 hours preparing (47%) for those interviews.

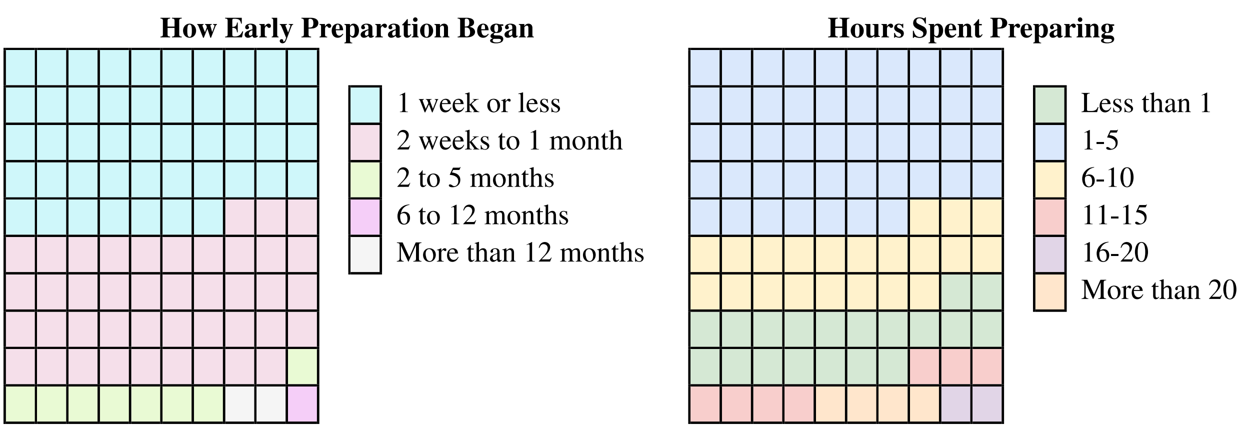


Figure 4: Breakdown of students' preparation for technical interviews, in terms of how early preparation began and the hours spent preparing, where each box represents 1%

### 5.1.3 How Personal Inputs may Impact Preparation

We considered how the preparation time spent may vary by gender, race, and ethnicity as shown in Table 4. To analyze the results, we applied Wilcoxon rank-sum tests, to compare those present in a population to those that were not within that group. We observed that females spent more time (in hours) than non-females did when preparing. Furthermore, White students began preparing earlier (in terms of time in advance), and spent more hours preparing than non-White students.

| | | *Not Female* | *Female* | | *Not HL* | *HL* | | *Not Black/ AA* | *Black/ AA* | | *Not White* | *White* | | *Not Asian* | *Asian* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Preparation Time** | ***p*-value** | **Mean** | **Mean** | ***p*-value** | **Mean** | **Mean** | **p-value** | **Mean** | **Mean** | ***p*-value** | **Mean** | **Mean** | ***p*-value** | **Mean** | **Mean** |
| How early did you begin preparing for technical interviews? | | | | | | | | | | .00 | 10.26 | 16.42 | | | |
| Before your interview(s), on average how many hours did you spend preparing? | .04 | 2.35 | 2.86 | | | | | | | .00 | 2.19 | 2.81 | | | |

*Note.* HL = Hispanic/Latinx; AA = African American

Table 4: Preparation time, with significance levels and the means of each group

## 5.2 *RQ2: How do differences in personal situations and cultural experiences impact preparation time for technical interviews?*

In this section, we consider what supports and barriers could impact preparation time. First, we describe the overall cultural experiences reported in our population (Section 5.2.1). Next, we compare the likelihood of different populations reporting certain cultural experiences in Section 5.2.2. Then in Section 5.2.3, we examine the impact of these cultural experiences on preparation time.

### 5.2.1 What Cultural Experiences Students Report

To assess the contextual influences proximal to choice behavior, we first wanted to define the cultural experiences that may impact students' availability for interview preparation. We chose to examine not only the positive variables which may lend themselves to support based on prior literature, but also those which may limit students' available time for interview preparation. We considered the barriers to be the time spent working in another job (either computing-related or non-computing related), as well as day to day experiences (caring for a child, caring for an adult, or recurring health problem). We considered having a home environment supportive of computing, and having friends in computing to be positive cultural experiences that could provide encouragement or bolster preparation. These groupings were based on the individual questions posed, as described in the Appendix.

In terms of the day to day cultural experiences, 5.9% of students reported caring for a child, 5.7% reported caring for an adult, and 6.1% reported having a recurring health problem. Next, we considered the number of hours spent working in either a computing related or non-computing related job. As shown in Figure 5, the majority of students did report spending some duration working a job, whether computing related (54%) or non-computing related (58%). In addition,

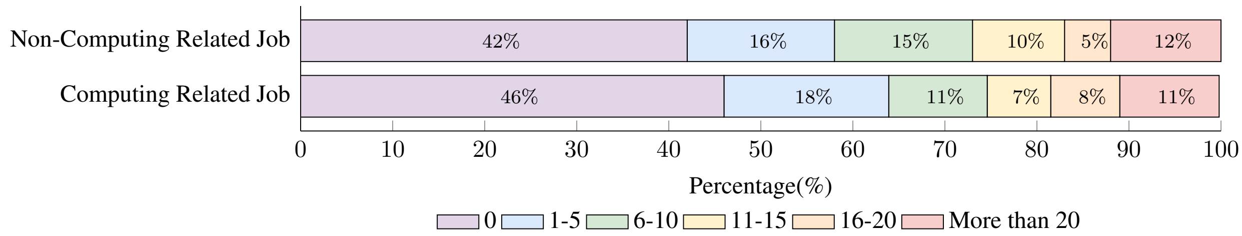


Figure 5: Hours students spend in computing and non-computing related jobs

12% of students reported working more than 20 hours on non-computing related jobs. Of which, 11% reported working more than 20 hours on computing related jobs.

In terms of the positive cultural experiences, we assessed the items that may lend themselves to increased social support. Considering the number of friends that students have in computing programs (Figure 6A), we observe that the majority of students report having 3-4. We also asked students how supportive their home environment was towards computing, using a Likert scale from “Not at all supportive” (0) to “Extremely Supportive” (4), as shown in Figure 6B. Most often, students reported that their home environment was extremely supportive (61.2%).

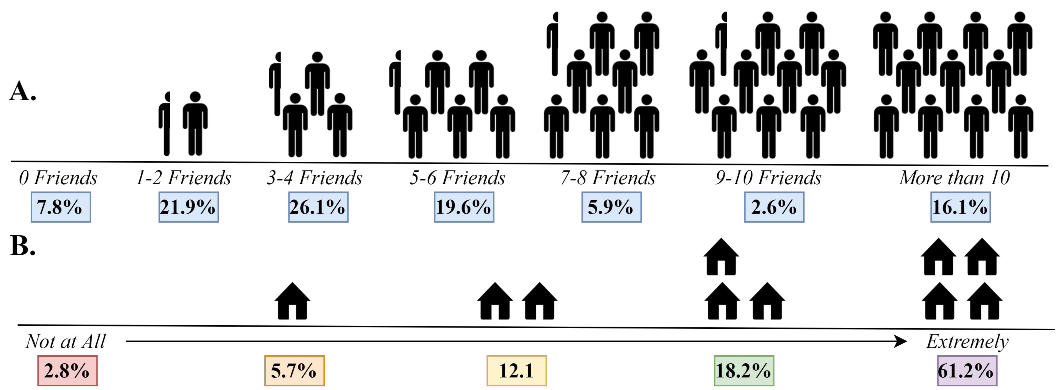


Figure 6: Number of friends students reported having in computing (A.), and how supportive their home environment is towards computing (B.)

### 5.2.2 Variations in Cultural Experiences by Gender, Race, and Ethnicity

Although we did examine the prevalence of cultural experiences across all students, such measures fail to account for the nuances that may exist between students of different genders, races, and ethnicities. Scholars have previously discussed the importance of applying critical race theory when conducting quantitative research to create a more accurate picture of individual experiences [46]. Therefore, to determine the impact of specific cultural experiences on different populations, we used Wilcoxon tests, as shown in Table 5.

We observed several key differences in the cultural experiences reported by students of different populations. When considering the day to day experiences, female, Hispanic/Latinx, and Black/African American students were all more likely to report caring for a child than non-female, non-Hispanic/Latinx, and non-Black/African American students. Females were also

| | | *Not Female* | *Female* | | *Not HL* | *HL* | | *Not Black/ AA* | *Black/ AA* | | *Not White* | *White* | | *Not Asian* | *Asian* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Cultural Experience** | ***p*-value** | **Mean** | **Mean** | ***p*-value** | **Mean** | **Mean** | ***p*-value** | **Mean** | **Mean** | ***p*-value** | **Mean** | **Mean** | ***p*-value** | **Mean** | **Mean** |
| Caring for a child | .02 | 0.05 | 0.10 | .00 | 0.04 | 0.10 | .02 | 0.05 | 0.13 | .04 | 0.07 | 0.04 | | | |
| Caring for an adult | | | | | | | | | | .01 | 0.07 | 0.03 | | | |
| Recurring health problem | .00 | 0.04 | 0.13 | | | | | | | | | | | | |
| Computing related jobs | | | | .00 | 4.85 | 6.60 | | | | .03 | 5.00 | 5.99 | | | |
| Non-computing related jobs | | | | .00 | 5.00 | 7.60 | .00 | 5.63 | 8.21 | | | | | | |
| Supportive home environment | .00 | 2.83 | 3.23 | .00 | 2.72 | 3.29 | | | | .00 | 2.55 | 3.40 | | | |
| Friends in computing | | | | .01 | 4.13 | 4.63 | | | | .00 | 3.80 | 4.97 | .00 | 4.12 | 5.32 |

*Note.* HL = Hispanic/Latinx; AA = African American

Table 5: Cultural experiences, results of Wilcoxon rank-sum tests with significance levels and the means of each group

more likely to have a recurring health problem ($p < .001$) than non-females. Also, White students were significantly less likely to report caring for a child, or an adult, than non-White students.

When considering the time spent on computing related jobs and non-computing related jobs we observed several significant differences. Hispanic/Latinx and White students spent more time on average working in a computing related job than non-Hispanic/Latinx and non-White students. Also, Hispanic/Latinx students and Black/African American students were more likely to spend increased time on non-computing related jobs than students not in those groups.

In terms of the positive cultural experiences, females were more likely to have a supportive home environment towards computing than non-females ($p < .001$). In addition, Hispanic/Latinx students reported more supportive home environments ($p < .001$) and had more friends in computing ($p = .008$) than non-Hispanic/Latinx students. White students were also higher in both measures than non-Whites ($p < .001$). Finally, Asian students reported having more friends on average than non-Asian students ($p < .001$).

### 5.2.3 Impact of Cultural Experiences on Preparation

To explore the impact the specific cultural experiences previously described on preparation, we ran Kruskal-Wallis tests (Table 6). We observed that the number of hours spent on computing related jobs, and non-computing related jobs significantly impacted how early preparation began, and the amount of time spent preparing (both $p < .001$). Furthermore, positive cultural experiences such as a supportive home environment, and the number of friends in computing also impacted preparation time (both $p < .001$). None of the day to day experiences reported significantly impacted preparation time. While they may not be a major contributor to differences observed in preparation time, this does not mean that they may not contribute, or still play a role. It is especially important to consider that the day to day experiences may also impact different groups of students in unique ways.

### *5.3 RQ3: How do differences in student preparation impact job attainment?*

We considered the number of job offers students have received as an important outcome (based on the performance domains and attainment in the SCCT model). The number of offers received was

| | *How Early Preparation Began* | | | | *Hours Spent Preparing* | | | |
|---|---|---|---|---|---|---|---|---|
| **Cultural Experience** | ***p*-value** | $\chi^2$ | $\epsilon^2$ | $\theta$ | ***p*-value** | $\chi^2$ | $\epsilon^2$ | $\theta$ |
| Computing related jobs | .00 | 143.25 | .19 | .36 | .00 | 124.14 | .17 | .33 |
| Non-computing related jobs | .00 | 19.34 | .03 | .12 | .00 | 18.62 | .03 | .12 |
| Supportive home environment | .00 | 31.38 | .04 | .15 | .00 | 32.55 | .04 | .15 |
| Friends in computing | .00 | 86.80 | .12 | .24 | .00 | 87.14 | .12 | .24 |

*Note.* Values were only included in the table if they were significant

Table 6: Kruskal-Wallis tests to examine cultural experiences impact on preparation time

based solely on students that reported having at least one interview (or more). As shown in Table 7, the majority of students did not receive an offer (62.0%), and among those students which did, students typically received one job offer (17.6% of students).

| **Number of Job Offers** | | | | | |
|---|---|---|---|---|---|
| *0* | *1* | *2* | *3* | *4* | *5 or more* |
| 62.0% | 17.6% | 10.8% | 6.2% | 1.2% | 2.1% |

Table 7: Number of job offers reported by students with at least 1-2 interviews, as percent of total students

To assess if there were any differences in the number of job offers between students of varied gender, racial, and ethnic backgrounds, we examined the total number of job offers, as shown in Table 8. Similar to preparation time, we observe that females received more job offers on average than non-females. Furthermore, White students received more job offers on average than non-White students.

| | | *Not Female* | *Female* | | *Not HL* | *HL* | | *Not Black/ AA* | *Black/ AA* | | *Not White* | *White* | | *Not Asian* | *Asian* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Preparation Time** | ***p*-value** | **Mean** | **Mean** | ***p*-value** | **Mean** | **Mean** | ***p*-value** | **Mean** | **Mean** | ***p*-value** | **Mean** | **Mean** | ***p*-value** | **Mean** | **Mean** |
| # of Job Offers | .00 | 0.69 | 1.02 | | | | | | | .00 | 0.64 | 0.92 | | | |

*Note.* HL = Hispanic/Latinx; AA = African American

Table 8: Job offers, with significance levels and the means of each group

Although the significance observed in females and White students suggested a link may exist between preparation and career attainment/outcomes, we wanted to validate this finding. Furthermore, no prior work has demonstrated empirical evidence of such a finding in computing (that we have encountered in our research). As shown in Table 9, we examined how the number of computing job offers and the time students report spending working in a computing related job (our dependent variables) were impacted by preparation time for technical interviews (the independent variables).

Preparation time, in terms of how early and how much time was spent, did significantly impact the number of computing job offers students received, and the number of hours they spent working in computing related jobs. When considering the number of job offers students received there was a large effect based on both $\epsilon^2$ and Freeman's $\theta$. As a control, we also analyzed how

| | # of Computing Job Offers | | | | Non-Computing Related Jobs | | | | Computing Related Jobs | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Preparation Time** | **p-value** | $\chi^2$ | $\epsilon^2$ | $\theta$ | **p-value** | $\chi^2$ | $\epsilon^2$ | $\theta$ | **p-value** | $\chi^2$ | $\epsilon^2$ | $\theta$ |
| How early did you begin preparing for technical interviews? | .00 | 323.24 | .44 | .56 | | | | | .00 | 143.41 | .19 | .39 |
| Before your interview(s), on average how many hours did you spend preparing? | .00 | 326.76 | .44 | .54 | | | | | .00 | 146.42 | .20 | .39 |

*Note.* Values were only included in the table if they were significant

Table 9: Kruskal-Wallis tests to examine the impact of preparation time on the number of computing job offers and hours spent in computing related jobs, with hours spent in non-computing jobs assessed as a control

preparation time impacted hours students spent in non-computing related jobs since the amount of time students spend preparing for technical interviews should not impact the time they spend working in another field. As anticipated, there was no significant effect for non-computing related jobs.

## 6 Discussion

Despite expectations and recommendations made (e.g., in preparatory books like Cracking the Code) that students should prepare for technical interviews months or even years in advance, our results reveal a very different picture of students' study habits [13]. Although 48% of students have not completed technical interviews, more than half reported completing one or more. Students who have completed at least one interview typically prepare 1 week or less (47%), followed by 2 weeks to a month (42%) beforehand. Therefore, only 11% of students are preparing earlier on. Meanwhile, 47% of students spend between 1 and 5 hours preparing, and 21% spend 6 to 10 hours. However, the results also display evidence of a system that is inherently flawed, predicated on treating students as a monolith with similar experiences and an equal time to commit to preparation.

Yet, not all students are given the same availability to prepare. As shown in Table 4, White students are more likely to begin preparing earlier than non-White students, and to spend more time (in terms of the number of hours spent) preparing. Nevertheless, the structures in place that allow White students to have more time are often shaped by cultural experiences, and other variables which may provide the availability to do so.

Scholars have noted that among the factors that are critical for broadening participation in computing, first-generation status, socioeconomic status, family characteristics, and how students finance their education can all play an important role [47]. They emphasized that is not enough to focus just on the gender and racial/ethnic identities of students, and mentioned that the familial background and whether or not they are the first to attend college in their family cannot be neglected [47, 48]. In terms of day to day experiences, White students were significantly less likely than non-White students to be caring for a family member (whether a child or an adult). Meanwhile, Hispanic/Latinx students and Black/African American students were all significantly more likely to be caring for a child than students who did not identify with those two groups.

Literature supports that White students are also less likely to need to work while in school [14], a finding supported by our Wilcoxon outcomes on non-computing related jobs. We observed that Hispanic/Latinx students and Black/African American students were more likely than students not in those groups to hold a non-computing related jobs. We also confirmed via Wilcoxon rank-sum test ($p < .001$) that in our population, those students which reported receiving federal student aid (referred to as having completed the Free Application for Federal Student Aid form, also known as FAFSA), worked significantly more hours on non-computing jobs ($M$ = 7.00, $SD$ = 8.04) than students that were not on FAFSA ($M$ = 4.15, $SD$ = 7.16). This information is relevant since it links student financial needs to more time spent working in a non-computing job, a factor which we illustrated does impact preparation ability. As shown in Table 6, time spent on non-computing jobs has a small effect (based on both the $\epsilon^2$ and Freeman's $\theta$) on how early preparation begins and on the hours spent preparing.

On the plus side, although Hispanic/Latinx students may not prepare significantly more than non-Hispanic/Latinx students, they do spend more time in computing related jobs. While there may be a financial motivation that influences how much time is spent working, this finding does also present a positive result, in terms of the performance domain and attainment. Our finding suggests that Hispanic/Latinx students may draw upon other factors, beyond the extent of preparation, to access navigational capital and succeed in the computing hiring process. One potential explanation could be that Hispanic/Latinx student are bolstered by social and familial support, and perhaps communication skills (related to linguistic capital). In our results, Hispanic/Latinx populations were significantly more likely to have a home environment that was supportive towards computing, and to have friends in computing, than non-Hispanic/Latinx students.

Leveraging social capital can serve as an important tool for students preparing for technical interviews. Students may work together with friends to study and prepare [41], to share information about what to expect, or to discuss challenges they face during hiring. Meanwhile, students may leverage familial capital to lean on families to discuss the stress of the hiring process, or to obtain encouragement despite obstacles.

Another advantage Hispanic/Latinx students may have, is that they may be bilingual or multilingual, and could leverage linguistic capital to obtain a computing position. It has been shown that communication skills are considered extremely important to employers, and are often assessed throughout the hiring process [16, 49–55]. Therefore, multilingual students, or those who have previously served as interpreters in their own family [49, 56, 57], may be more adept at sharing their work and explaining their code during technical interviews.

We would also like to call attention to females, a group traditionally underrepresented in computing, which displayed some positive findings despite barriers. Although females were more likely to be caring for a child or to report a recurring health problem, they spent more time preparing for technical interviews and they received more job offers than non-females. In the context of CCW, we suggest females may utilize resistant capital to "enact their agency to oppose power structures" [41, p. 8] and to challenge stereotypes and notions of a male dominant field. We also hypothesize that females leverage aspirational capital despite obstacles, to prepare more, since they value their student identity, and want to enhance computer control. Previous literature has shown that obtaining control is obtained by mastery, and perceptions of having power over computers [32]. This computing control in turn results in stronger computer self-efficacy. While in general males are considered to have a higher computing affect [58, 59], in terms of reduced anxiety and increased enjoyment, females may use preparation as a tool for ameliorating technical interview stress or anxiety, and working to develop control over the subject. In the context of SCCT, it is ultimately the outcome expectations of succeeding, and goal of obtaining a career in computing that drives the commitment to enhanced interview preparation, despite the contextual influences that may pose barriers, and that ultimately yields performance attainment.

Taken together our findings demonstrate that students' cultural experiences, interview preparation, and job attainment in computing do tend to vary. While there is a relationship between person inputs and the contextual influences proximal to choice behavior, the actions taken to start a career in computing differ based on supports and barriers, as well as components unexamined directly here, such as self-efficacy, outcome expectations, and computing interest. However, these results also show that there is an opportunity for educators and the computing industry to educate themselves, and to evolve.

Going forward, there are multiple ways for universities and academic institutions to provide increased support, opportunities, and to help students to prepare for the hiring process in computing. Although it is not feasible to constantly revise the curriculum to suit the needs of industry, there are steps that can be taken. For universities and faculty, modifying courses to supplement theoretical understanding with more practical examples could lead to richer understanding. Additionally, we suggest considering the inclusion of a course to develop students' critical thinking, problem solving, and soft skills, and to provide preparation for long term success (either in industry or in academia). The course could include practice with different kinds of coding problems, such as those given on LeetCode and HackerRank, and perhaps mock interviews to help students manage their anxiety and to enhance their communication. We also recommend preparing students earlier in their studies, making sure to raise awareness of expectations and letting them know what resources they can use (such as the school's career center, or preparing using books like Cracking the Coding Interview). Encouraging internships and regular interview practice throughout schooling, could provide a more level playing field for all students when they do begin applying for jobs.

In addition, industry can also work towards making the hiring process more equitable. As shown in this work, preparation time required to succeed in technical interviews requires a huge overhead for students, and not all students have the same amount of time to prepare. As such, we encourage industry to reconsider the methods it uses for evaluation. Focusing on take home assignments to examine technical prowess, or asking students to describe projects they have contributed to, and their role in the work, could serve to provide an insight into technical capabilities without necessitating the same kind of preparation. Alternatively, providing students with questions reflective of the types of problems they might actually encounter in the future role could offer better insight into future performance. However, it may take time to revise corporate policies, expectations, questions, and interview practices that impact how job candidates are assessed. In the short term, we suggest companies begin with offering all candidates transparency on what to expect, perhaps even providing study guides or sample problems, so that busy students can focus efforts. In this way, students could still take their own approach at problem solving, but they could at least scope their efforts and expectations on what could be covered, rather than having to guess or to try to review material on all different programming languages and computing topics.

## 7 Limitations

The findings from this investigation are limited in several ways. First, prior research has emphasized the importance of considering intersectionality and its impact on the experiences and challenges students and professionals face in computing fields [56, 60, 61]. Yet due to the large amount of individuals belonging to multiple racial/ethnic groups, we chose not to examine intersectionality in this analysis. Statistics regarding each race/ethnicity and gender identity affiliation were based on the students' self-reports, and were analyzed as a Boolean measure of either identifying with the group or not, rather than considering overlapping identities described by the dataset. However, intersectionality could play a role in the preparation time, cultural experiences, and job attainment, and future work may want to explore this area further to obtain a more nuanced overview. In addition, while we did not have a large enough sample to do so, going forward it would be valuable for researchers to explore those on the gender spectrum (i.e., analyzing students that identify as transgender, agender, or a gender not listed).

While we observe differences in the preparation time spent and the number of job offers for White students and non-White students, and females and non-females, and we do observe correlations that may influence these values, we cannot infer direct causality without additional inquiry. Although quantitative analysis can provide valuable insights, it is limited in its ability to delve deeper into selected variables. In addition, there may be other variables which we did not consider which may contribute to preparation or job attainment (e.g., GPA), and additional supports as well. Going forward, we recommend that qualitative interviews with students are conducted to confirm and further determine what factors underlie preparation time, and its impact on the hiring process and job offers.

## 8 Conclusions

In this research, we applied SCCT and CCW to examine the results of a survey on students' person inputs, contextual influences, actions, and performance domains and attainment in the context of technical interviews. Our findings provide insight into students' preparation habits, the cultural experiences that may provide supports or barriers to preparation, and the how preparation impacts job attainment. We found that White students and females, began preparing earlier and spent a longer time preparing than non-White students and non-females. However, other variables such as commitments from other jobs can impact the amount of time that students have to spend. While additional factors (not examined here) may also contribute to job attainment, making assumptions about students' availability to prepare is unfair to those who do not have ample time, and contributes to inequity.

Although diversity in the computing workplace is slowly improving, oppressive systems need to be dismantled in order to make collective progress. It is important to consider ways to improve the hiring process, such as practices predicated on all students having the same availability to prepare. Refining the process to give all candidates equal opportunities to demonstrate their capability, could help companies build teams more reflective of the diversity in the general population. Apart from the economic and social justice imperatives to broadening participation in computing fields, there are several professional incentives to doing so. Research has indicated that creating more diverse teams of software engineers heightens intellectual variation (in terms of the unique perspectives), and increases innovation, productivity, and product quality [62–64]. As such, companies should also recognize that students from diverse backgrounds may leverage different capital that could contribute to the team.

To truly celebrate the traits that make each individual an asset, it is necessary to play to the strengths of all populations. The evolution of technical interviews into an almost examination-like atmosphere may have its benefits in terms of hard skill assessment, but it does not necessarily provide a level playing field. Rather than preparing for the job itself, students become adept at answering questions that do not mimic the responsibilities held in the day to day of the role. The current system also requires ample studying, and additional complexities contribute to inequality in time available to prepare. Companies must consider revisions to current practices, and expanding how technical skills are assessed beyond the current inequitable methods of evaluation. Universities and educators should also be mindful of the expectations placed on students and should consider how they can help students to best prepare for a career in the field.

In the future, qualitative inquiry could be used to further examine students' experiences with the hiring process. In addition, researchers could delve further into exploring how students leverage their own inherent capital to overcome obstacles. Although there is still much to learn, through better understanding of what helps students to succeed, we can reform existing structures to create a more egalitarian, transparent, and inclusive hiring process.

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## A Survey Instrument

We have included the questions from the survey that are relevant for this research.

| Question Asked | Response Options | Response Scale |
|---|---|---|
| What year are you in college? | $1^{st}$ year, $2^{nd}$ year, $3^{rd}$ year, $4^{th}$ year, past $4^{th}$ year | Select One |
| How many programming or technical job interviews have you completed in computing? | 0, 1-2, 3-4, 5-6, 7-8, 9 or more | Select One |
| How many job offers have you received in computing? | 0, 1, 2, 3, 4, 5 or more | Select One |
| How early did you begin to prepare for technical interviews? | 1 week or less, 2 weeks to 1 month, 2 to 5 months, 6 to 12 months, More than 12 months | Select One |
| Before your interview(s), on average how many hours did you spend preparing? | Less than 1, 1-5, 6-10, 11-15, 16-20, More than 20 | Select One |
| For any of the technical interviews you have participated in, how were you recruited for the position? Mark all that apply. | • Applied Online<br>• Personal Referral<br>• Recruiter<br>• Campus Recruiting<br>• Career Fair<br>• Hackathon or Programming Competition<br>• Contact through Social Media (e.g. LinkedIn, Facebook, etc.)<br>• Contact through Software Development Site (e.g. GitHub)<br>• Through Professional Organization<br>• Through Coding Bootcamp<br>• In Person<br>• General Job Portals/Search Engines (e.g., CareerBuilder, Glassdoor, SimplyHired, We Work Remotely, Indeed)<br>• Other (Text entry) | Select All, with Text Entry |
| What resource(s) did you use to prepare for your technical interview(s)? Mark all that apply. | • No Preparation<br>• Online Coding Resources (e.g. LeetCode or HackerRank)<br>• Preparatory Books (e.g. Cracking the Code)<br>• Self Study of Textbooks<br>• Course Notes or Assignments<br>• Mock Interviews<br>• Projects Outside School/Work<br>• Other (Text entry) | Select All, with Text Entry |

Table 10: Survey questions and responses used in our analysis

| Question Asked | Response Options | Response Scale |
|---|---|---|
| How supportive is your home environment towards computing? | | Likert Scale (5-points): Not at all supportive to Extremely supportive |
| How many friends do you have in computing? | 0, 1-2, 3-4, 5-6, 7-8, 9-10, More than 10 | Select one |
| How many hours do you work on computing related jobs outside the home each week? | 0, 1-5, 6-10, 11-15, 16-20, More than 20 | Select One |
| How many hours do you work on non-computing related jobs outside the home each week? | 0, 1-5, 6-10, 11-15, 16-20, More than 20 | Select One |
| Which of the following apply to your day-to-day life? Mark all that apply | • Caring for a child (e.g. sibling, your own child)<br>• Caring for an adult (e.g. grandparent)<br>• Personal recurring health problem (not including common illnesses like a cold or flu)<br>• Other (Text Entry) | Select All, with Text Entry |
| With which racial and ethnic group(s) do you identify? | • American Indian or Alaska Native<br>• Asian<br>• Black or African American<br>• Hispanic, Latinx, or Spanish origin<br>• Middle Eastern or North African<br>• Native Hawaiian or Other Pacific Islander<br>• White<br>• Another race or ethnicity not listed above | Select All |
| How do you describe your gender identity? | • Female<br>• Male<br>• Agender<br>• Transgender<br>• A gender not listed<br>• Text entry | Select One, with Text Entry |

Table 11: Survey questions and responses used in our analysis