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FLORIDA INTERNATIONAL UNIVERSITY

Miami, Florida

TECHNICAL INTERVIEWS: ANOTHER BARRIER TO BROADENING PARTICIPATION IN COMPUTING?

A dissertation submitted in partial fulfillment of the

requirements for the degree of

DOCTOR OF PHILOSOPHY

in

COMPUTER SCIENCE

by

Stephanie Lunn

2021

To: Dean John L. Volakis
College of Engineering and Computing

This dissertation, written by Stephanie Lunn, and entitled Technical Interviews: Another Barrier to Broadening Participation in Computing?, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

Peter Clarke

Leonardo Bobadilla

Mark Allen Weiss

Kathleen Quardokus Fisher

Monique Ross, Major Professor

Date of Defense: May 26, 2021

The dissertation of Stephanie Lunn is approved.

Dean John L. Volakis
College of Engineering and Computing

Andrés G. Gil
Vice President for Research and Economic Development
and Dean of the University Graduate School

Florida International University, 2021

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DEDICATION

This dissertation is dedicated to my family and friends for their endless love, support, and encouragement.

With special gratitude to my husband, Patrick Lunn.

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I would like to acknowledge and thank the numerous individuals who contributed to this research — my mentors, my committee, my colleagues, my friends, my family, and my interview participants. First and foremost, I would like to say how grateful I am for my advisor, Dr. Monique Ross. Thank you for always making time for me, for answering my many questions, for pushing me to do more and be better, for your guidance, and for always finding the rainbow after the storm. Your encouragement, optimism, and passion to impact positive change is infectious, and I could never have done this without you. You demonstrate that it is possible to do it all, and you truly are a leader and an inspiration.

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Finally, I would like to express my gratitude to the participants of my study, who volunteered their time, and were willing to share their experiences. I am forever indebted to you. I enjoyed our conversations immensely, and your persistence are strength are motivational.

ABSTRACT OF THE DISSERTATION

TECHNICAL INTERVIEWS: ANOTHER BARRIER TO BROADENING PARTICIPATION IN COMPUTING?

by

Stephanie Lunn

Florida International University, 2021

Miami, Florida

Professor Monique Ross, Major Professor

What does it take to obtain a computing position in the industry? Although anecdotal reports state that "hiring is broken," empirical evidence is necessary to identify the flaws in the existing system. The goal of this dissertation was to understand what expectations companies have for job seekers in computing, and to explore students' experiences with technical interviews and their pathways to job attainment. In particular, this work considered how hiring practices may impact populations already underrepresented in computing such as women, Black/African American students, and Hispanic/Latinx students. It also sought to understand how minoritized populations leverage their own inherent capital to overcome obstacles throughout the process. The theoretical frameworks of community cultural wealth, social cognitive career theory, identity theory, and intersectionality guided the studies, to answer the following research questions: 1) What does the hiring process in computing look like from both the applicant and industry perspective?; 2) How do cultural experiences impact technical interview preparation?; 3) How do technical interviews, and other professional and cultural experiences impact computing identity?; and 4) How do students describe their experiences with the hiring process in computing?

To address these questions, a variety of methods were employed, beginning with a systematic literature review. This was followed by an explanatory sequential mixed-methods design that utilized a survey, statistical analysis, and semi-structured interviews. Discursive phenomenography was also the methodology chosen which shaped the qualitative inquiry. The findings illustrated the unique experiences and support mechanisms students from different gender, racial, and ethnic backgrounds utilize to succeed in hiring. These results not only serve to inform students, educators, and administrators how to best prepare for technical interviews, but also present a call to action for industry to change hiring and workplace practices that limit diversity. Suggestions and guidelines are given to enable a hiring process that can still achieve its target of finding qualified employees, but that does so in a manner more inclusive to all job seekers.

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LIST OF ABBREVIATIONS

ACM	Association for Computing Machinery
ASEE	American Society for Engineering Education
CCW	Community Cultural Wealth
CE	Computer Engineering
CFA	Confirmatory Factor Analysis
CS	Computer Science
DEI	Diversity, Equity, and Inclusion
FAFSA	Free Application for Federal Student Aid
GPA	Grade Point Average
HBCUs	Historically Black Colleges and Universities
HSIs	Hispanic-Serving Institutions
ICT	Information and Communication Technology
IEEE	Institute of Electrical and Electronics Engineers
IS	Information Systems
IT	Information Technology
ML	Machine Learning
NSBE	National Society of Black Engineers
RQs	Research Questions
SLR	Systematic Literature Review
SHPE	Society of Hispanic Professional Engineers
STEM	Science, Technology, Engineering, and Mathematics
TIs	Technical Interviews
URMs	Under-Represented Minorities
UPE	Upsilon Pi Epsilon

CHAPTER 1

INTRODUCTION

1.1 Statement of the Problem

Across all areas of employment in the United States (U.S.), occupations in computing and information technology are some of the fastest growing [U.S. Bureau of Labor Statistics, 2021a]. Over the next decade, they are projected to continue to rise 11%, a rate higher than other professions. Yet, despite the ongoing need to fill these roles, there is a shortage of computing graduates in general, but also a dearth of women, Blacks/African Americans and Hispanics/Latinxs [U.S. Bureau of Labor Statistics, 2021b, U.S. Census Bureau, 2019, McAlear et al., 2018].

Men, Whites, and Asians are inordinately represented in computer and mathematical positions in the U.S. [U.S. Bureau of Labor Statistics, 2021b], incommensurate to proportions in the population (Figure 1.1) [U.S. Census Bureau, 2019]. Although men are just under half of the population in the U.S., across all computer and mathematical occupations they are 74.8% of the total workers. Meanwhile, Whites represent 76.3% of the total population, and 60.1% when considering the White (not Hispanic) designation [U.S. Census Bureau, 2019]. However, they comprise one of the largest majorities at 64.5% in computer and mathematical occupations.

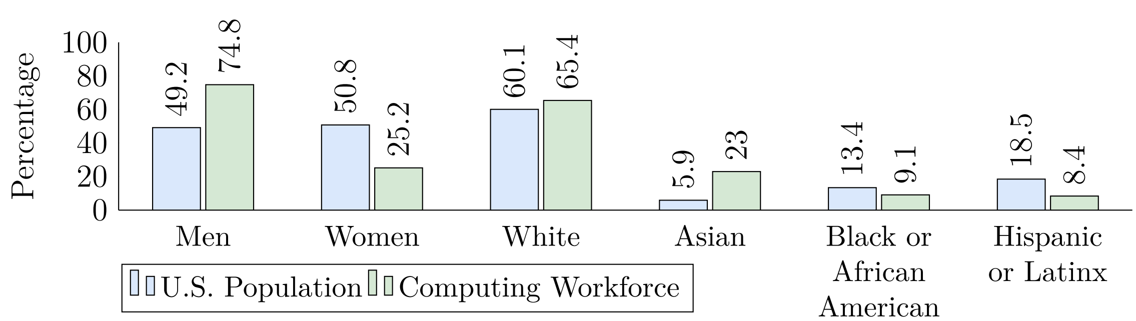


Figure 1.1: Demographics in the U.S. relative to representation in computer and mathematical occupations

When considering specific roles in computing fields — referring to computer science (CS), computer engineering (CE), and information technology (IT) — the situation is also problematic [U.S. Bureau of Labor Statistics, 2021b, U.S. Census Bureau, 2019], as shown in Figure 1.2. Software developers are most often men (80.6%), and White (57.5%) or Asian (34.1%). The same is true of computer programmers. Among the roles examined by the report, women are most likely to serve as database administrators and architects (28.8%). Meanwhile, Black or African Americans (11.9%) and Hispanic or Latinx (15.8%) workers both reach representation levels closest to the U.S. population in information security analyst positions. While women, Black/African American, and Hispanic/Latinx workers may be present in each area shown, their overall representation never reaches that of the general population. Therefore, to ameliorate this inequity, it is useful to examine the variables that may contribute to engagement and retention.

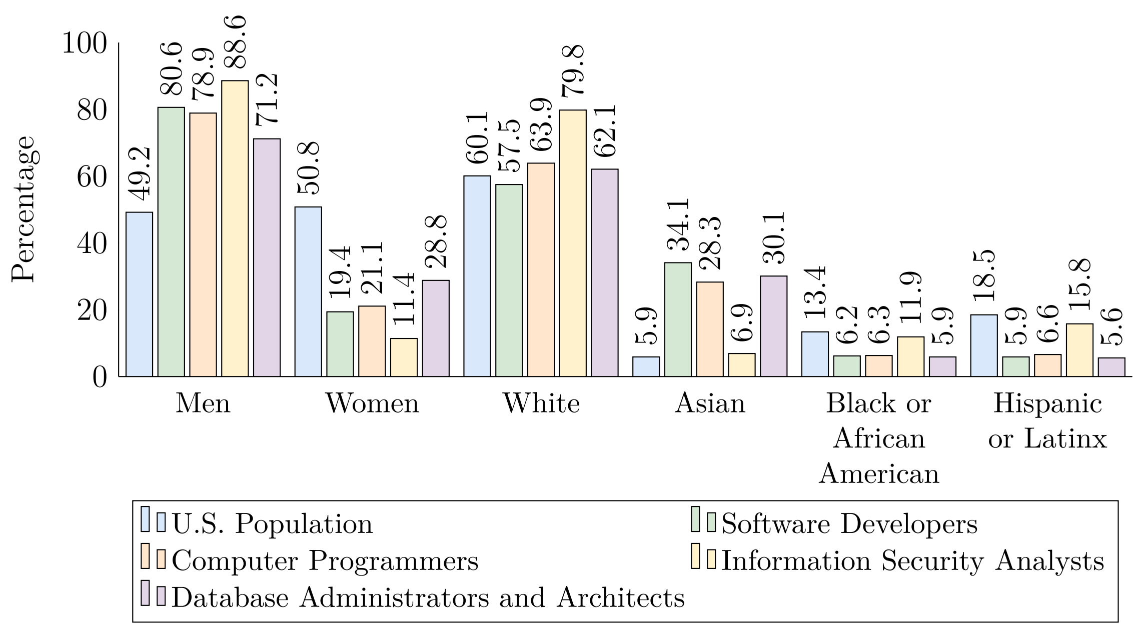


Figure 1.2: Demographics in the U.S. relative to specific roles in computing

Along with deficiencies and inequities in representation, two additional concepts are particularly important to understanding the full impact of the problem, broadening participation and graduate employability. I define broadening participation and discuss issues noted in the literature in Section 1.1.1. Then, in Section 1.1.2 I discuss issues surrounding struggles with post-graduation job attainment in computing.

1.1.1 Broadening Participation

There are issues engaging and retaining women, and Black/African American and Hispanic/Latinx students and workers in computing [Lunn et al., 2021c, Zahedi et al., 2021, U.S. Bureau of Labor Statistics, 2021b]. Although academia and industry have both sought understanding, and ways to remedy these concerns, disparities remain ongoing. Along these lines, *broadening participation* is a term used to describe

> meaningful actions that address the longstanding underrepresentation of various populations including women, racial/ethnic minorities (African Americans/Blacks, Hispanic Americans, American Indians, Alaska Natives, Native Hawaiians, Native Pacific Islanders), persons from economically disadvantaged backgrounds, and persons with disabilities, in the computing field. [National Center for Women and Information Technology, 2019, p. 7]

Minoritized populations may face impediments that could deter them from computing at multiple stages of life [Fisher and Margolis, 2002, Trauth et al., 2016]. Although there may be many potential reasons, often underrepresentation is attributed to having a lack of early access, role models, and encouragement [Frenkel, 1990, Cheryan and Plaut, 2010, Guzdial et al., 2012]. Early formal and informal exposure have also been shown to play a crucial role in increasing interest and curiosity in Science, Technology, Engineering, and Mathematics (STEM), and to promoting computing as a field of study [Goode et al., 2006, McCormick, 2019]. Accordingly, there has been a rise in groups such as Girls Who Code and Black Girls Code, to increase exposure to computing from a younger age [Modi et al., 2012, Kaiser, 2019].

Stereotypes depicting computer science majors and programmers as “geeky” White males are said to further exacerbate the problem, alienating those who do not fit this mold, and resulting in a lack of sense of belonging and confidence [Margolis et al., 2000, Fisher and Margolis, 2002, Varma, 2007b, Beyer, 2014, Cheryan and Plaut, 2010, Mejias et al., 2019, Ensmenger, 2015, Rodriguez and Lehman, 2017]. To close achievement-gaps and dismantle issues of equity, minoritized students must receive proper support, encouragement, and recognition, challenging traditional conceptions about “what” and “who” professionals in STEM should be or look like [Varelas et al., 2012, Visintainer, 2014, Hughes et al., 2020, Wong and Kemp, 2018].

Once enrolled or employed in computing, different obstacles arise such as inhospitable work and academic environments, unconscious biases, and feelings of isolation [Dee and Gershenson, 2017, Corbett and Hill, 2015, Hewlett et al., 2008]. Undergraduate Latinas and Black women in STEM fields have reported multiple instances of compounded discrimination based on their gender, racial, and ethnic identities [Johnson, 2011, Rodriguez and Blaney, 2020]. Furthermore, in academic environments, where teamwork is required for laboratory work, assignments, and/or study groups, women of color report feeling excluded [Tate and Linn, 2005, Johnson, 2007, Malone and Barabino, 2009]. They also report being left out from informal socialization and networking, where information about potential internships, scholarships, and research opportunities are discussed [Tate and Linn, 2005, Foor et al., 2007, Malone and Barabino, 2009]. Such concerns are linked to feelings of isolation, a reduced sense of belonging, and marginalized social identities [Johnson, 2012, Rodriguez and Blaney, 2020]. Unconscious or implicit bias may occur despite conscious efforts to reject stereotypes, and frequently manifest in less overt ways such as in-group favoritism [Buse et al., 2017]. However, providing encouragement has been shown to play a role in students' ability, satisfaction, and likelihood to pursue a career in computing [Guzdial et al., 2012].

Social support (which includes role models, family members, and peers) is considered important for students' engagement and persistence [Mejias et al., 2019]. In computing, role models may include academics, professionals, or other students, and they are beneficial for engaging students in the discipline [Grande et al., 2018]. Furthermore, peer support can be essential for computer science students' interest, success, retention, and feelings of connectedness and competence [Lotkowski et al., 2004, Haungs et al., 2012, Hughes et al., 2020, Mejias et al., 2019]. Using "pair" or "peer" programming, a technique by which students work together to accomplish a programming task, not only improves enjoyment, but also retention [Williams et al., 2000, Carver et al., 2007]. Additionally, sense of belonging is noted as affecting students' perception of their own abilities, perhaps even more so than students' actual performance [Veilleux et al., 2013]. Having both academic and non-academic social support and conversations can influence the attitudes held towards their abilities. Furthermore, qualitative studies of undergraduate women have demonstrated that for women to choose to major in computer science, it is important for them to have friends and other support that encourage their choice to pursue the field [Cohoon, 2002].

Additionally, Black women report feelings of cultural isolation and exclusion in computing, and Black males report that identification with computing is not part of the social norms within their peer group [DiSalvo et al., 2011, Charleston et al., 2014]. Such "disidentification" is considered a deterrent both for academic outcomes and for professional growth [DiSalvo et al., 2011]. Furthermore, interviews with Latina students in computing pointed to a cultural component unique to this population — the difference between individualist versus collectivist mindsets [Rodriguez and Blaney, 2020]. In this study by Rodriguez and Blaney (2020), one of the subjects mentioned that often computing fields lend to antisocial behaviors and that typically students work alone. This particular finding has impacts not only for sense of belonging, but also highlights a key difference in cultural backgrounds between Latinx students and others. It has been demonstrated that Latin cultures tend to be more group-oriented, and to place more emphasis on the community and cooperation, a psychosocical construct known as collectivism [Arevalo et al., 2016]. Thus, for Latinx students, being part of a major where others may prefer to work alone could impact performance and retention. To combat such feelings of dissonance, peer support can be a tremendously positive influence [Mejias et al., 2019]. Students in computing at historically Black colleges and universities reported higher levels of social support, greater outcome expectations, and elevated academic and coping self-efficacy than students at predominantly White institutions [Lent et al., 2011].

In regards to the workforce, many organizations and major technology companies (e.g., Amazon, Apple, Facebook) are aware of the skewed representation in computing, and they are taking steps to ameliorate the situation [Williams, 2014, Aspray, 2016, Hall Jr and Gosha, 2018, Amazon, 2019, Google, 2020, Apple, 2021]. Although this may take many forms, an example of these efforts includes increasing partnerships and outreach. Google established the Computer Science Summer Institute (CSSI), a “camp” to engage high school seniors in the discipline earlier[1]. They also offered a branch specifically for Historically Black Colleges and Universities (HBCUs) to help students build their support network and to increase retention in the field. In January 2021, Girls Who Code[2] held its inaugural career fair event to connect the community with job opportunities [Girls Who Code, 2021]. In addition, companies may send recruiters to conferences intended to provide networking and professional development for minoritized populations such as the National Society of Black Engineers[3] (NSBE), the Society of Hispanic Professional Engineers[4] (SHPE), and the Grace Hopper Celebration of Women in Computing[5]. Alternatively, companies may offer affinity groups created and led by employees (e.g., Amazon has 12, including groups such as the Black Employees Network and Glamazon for LGBTQIA+ employees and their allies [Amazon, 2019]). However, ongoing declines in representation, and regular reports regarding discrimination faced and a lack of equity in management or advancement opportunities indicate there is still a long way to go [Peckham et al., 2007, Mandel and Carew, 2015, Bloomberg News, 2020, Google, 2020, Facebook, 2020, Kraus, 2020]. As a result of some of these issues described, attrition of minoritized populations in technology positions remains an ongoing concern [Hewlett et al., 2008, Ashcraft et al., 2016]. Although such barriers are well documented [Payette, 2018, Ashcraft et al., 2016], finding ways to ensure equity and to create more inclusive practices and environments is more challenging.

[1] https://buildyourfuture.withgoogle.com/programs/computer-science-summer-institute/

[2] https://girlswhocode.com/

[3] https://www.nsbe.org/

[4] https://www.shpe.org/

[5] https://ghc.anitab.org/

Attempts to broaden participation have taken many forms, from examining students' social support and sense of belonging to companies pledging their support. Yet, an important step in broadening participation is the transition from being a student to an employee. Along these lines, it is vital to consider the role that the hiring process may play in perpetuating inequalities [Hall Jr and Gosha, 2018, Google, 2020, Facebook, 2020, Kraus, 2020]. Understanding the full impact of the hiring process in computing, and in particular, how it affects groups already underrepresented in computing (females, Black/African American, and Hispanic/Latinx workers), is important to creating a workplace of diverse talent [Ashcraft et al., 2016, Aspray, 2016, Hall Jr and Gosha, 2018].

1.1.2 Graduate Employability

Graduate employability is a term used to describe a student's ability to obtain a job, to maintain that position, and then to find another [Suleman, 2018]. However employability may also depend upon "knowledge, skills and attitudes; the way these assets are used and deployed; the presentation of assets to potential employers, and context within which the individual works (for example labour market and personal circumstances)" [Wickramasinghe and Perera, 2010, p. 226]. Propelled by the needs of the workforce, as well as regional, national, and supranational agencies, universities are increasingly under pressure to find a balance between education and professional training, and graduate employability is often linked to performance metrics [Boden and Nedeva, 2010, McCowan, 2015, Matherly and Tillman, 2015, Bennett et al., 2017, Suleman, 2018]. Frequently institutions focus employability efforts through campus career services, although they may also seek to develop employability through degree programs, enterprise support, undergraduate research programs, industry insight programs, and credit/non-credit bearing opportunities [Bennett et al., 2017].

Despite rising industry needs to fill vacancies in computing, and institutional efforts to improve employability, many new graduates struggle to obtain a job [Edwards et al., 2009, Almi et al., 2011, Hall Jr and Gosha, 2018, Lara et al., 2019]. In fact, students completing a degree in a computing field have been shown to have the "highest unemployment rates of all subjects, six months after graduation" [Fincher and Finlay, 2016]. In part, such discrepancies are attributed to graduates inability to sufficiently perform during the hiring process, where computing candidates are required to demonstrate a combination of hard (technical) and soft (non-technical) skills to succeed [Fincher and Finlay, 2016, Radermacher, 2012].

While the reasons students struggle may vary, multiple publications consider the disconnect between formal education and industry expectations [Radermacher and Walia, 2013, Oguz and Oguz, 2019]. Along these lines, industry professionals, researchers, and educators have noted that often computer science students may have gaps in their understanding and in their ability to transfer knowledge from the fundamental and theoretical concepts learned in classrooms [Lethbridge, 1998, Brechner, 2003, Carver and Kraft, 2011, Radermacher, 2012, Radermacher and Walia, 2013]. These studies consider what is expected from job applicants, and try to reconcile how it aligns against what is needed to pass an interview, and in the future career. Specifically, Radermacher calls this phenomena a *knowledge deficiency*, and defines it as the absence of a skill, ability, or knowledge for a recent computer science graduate of a concept that employer would otherwise expect them to have [Radermacher, 2012]. Balancing academic curriculum requirements and meeting industry needs can be a challenge for universities, but it can also play a critical role in students' preparedness.

Despite ongoing discussions and suggestions from both academia and industry, neither side seems to have a concrete way to better prepare applicants for hiring [Oguz and Oguz, 2019]. While universities are not intended to serve as trade schools, they do want to support students' academic progression, and it is still a vital outcome to instill the principles and foundations in computing adequately [Fincher and Finlay, 2016]. On the other hand, it should be cautioned that what universities cover and industry want may not always align. Industry often faces pressure to accommodate rapid advancements in technology to remain globally competitive, and such quick turnover may be infeasible to accommodate within the scope of more rigid academic curriculum [Ankrah and Omar, 2015, Wright et al., 2008].

1.2 Background

A *job applicant* is defined as someone who applies for a job. If a job applicant's qualifications are deemed sufficient for the requirements of a particular job posting, and they are under consideration for the role, they become a *job candidate*. Job candidates typically undergo some kind of interview, and then if the person or group of people looking to fill the position feels the job candidate is the best fit and/or will perform well, they will offer them the position. If this person accepts, and then starts working for the institution, agency, company, organization, business, association, or firm, they then become an *employee*. Throughout this work, the phrase *job seeker* is another term that may be encountered, and which encompasses both the job applicant and job candidate titles, as it is broadly meant to refer to someone trying to obtain a role in the industry, or with a particular institution, agency, company, organization, business, association, or firm. Students, and those interested in positions that may not have had a formal education in computing, may be a job applicant, job candidate, job seeker, or employee, depending on where they are in the hiring life cycle.

There are two additional concepts which should be defined to describe the hiring process in computing and its interpretation — experiences and technical interviews. In Section 1.2.1, I present experiences in general, and then specifically describe cultural and professional experiences. Then, I define technical interviews, and what makes them so challenging for computing students in Section 1.2.2.

1.2.1 Experiences

Broadly *experience* is defined as the knowledge, understanding, and skills that result from events, activities, and/or interactions with others [Fisher et al., 1997, Peters et al., 2014]. Different types of experiences have been suggested to be instrumental in helping to recruit and retain students in various STEM disciplines. For example, mentoring and advising are experiences that demonstrated value for the development of both undergraduate and graduate students in all fields of study [Belcher, 1994, Kelly and Schweitzer, 1999, Patton and Harper, 2003, Pascarella and Terenzini, 2005, Patton, 2009, Griffin et al., 2010]. These examples of academic experiences, along with other professional and cultural experiences, can have an immense impact on students' decision to persist in the discipline, and to ultimately pursue a career in computing.

This dissertation will primarily focus on students' professional and cultural experiences. *Professional experiences* have been described as the "interactions, situations, and events individuals encounter while serving in a particular workplace role" [Klein, 2016], and also include skill development (e.g., training/leadership opportunities), defining career goals, and/or networking [Worthen, 2005]. Here, the definition is extended to include the hiring process for roles, and to specify the development of computing skills (e.g., participating in coding bootcamps or freelance computing-related jobs). Meanwhile, *cultural experiences* are defined as the knowledge learned and shared, for which activities, behaviors, and the interpretation of experiences define everyday life [Adelman, 1988, McCurdy et al., 2004, Cultuur, 2014]. Items considered include day-to-day responsibilities (e.g., caring for others) and social support (e.g., home environment, role models, and peers).

Although each separate experience may not entirely alter how a student feels about computing, engaging in a combination of experiences could contribute to a broader impression of the field. Previously Jackson and Seiler have described how experiences may accumulate to "thicken" and reinforce identity [Jackson and Seiler, 2013]. It is this notion of accumulated individual experiences that contribute to a growing (or eroding) disciplinary identity which propels the focus of this dissertation. I seek to understand the impact of students' experiences with the hiring process, as well as other professional and cultural experiences.

1.2.2 Technical Interviews

Although technology companies have created diversity programs/initiatives, and have worked to improve their recruitment and retention practices, issues still remain [Barr, 2017, Farnsworth and Holtzblatt, 2016, Mandel and Carew, 2015, Hall Jr and Gosha, 2018, Rodriguez and Lehman, 2017]. 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 [Gosha et al., 2019]. 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. Specifically, *technical interviews* refer to part of the hiring process for a computing position that occurs online, via phone/video call, or on-site/in-person, and that includes any combination of problem solving, logic, live coding, and/or programming tests to be performed by job candidates [Ford et al., 2015, Behroozi et al., 2020a, Behroozi et al., 2018, McDowell, 2015]. Throughout the process, candidates are encouraged to describe their thinking and are expected to consider the optimal performance of their solution, referred to as the time complexity. Despite intentions of using these extemporaneous coding challenges to assess programming capabilities, being expected to simultaneously present a solution while speaking through the thought process is not only challenging from the examination standpoint, but it can also be cognitively taxing [Behroozi et al., 2018].

Currently, there is limited research surrounding this phenomena; however, digital forums, informal accounts, blogs, and preparation guides are rife with horror stories and descriptions of the Herculean expectations [Aziz et al., 2012a, Behroozi et al., 2019, McDowell, 2015]. In order to meet the largely unwritten demands these interviews require, applicants are expected to prepare for hours each week, over the span of many months, or even years [Aziz et al., 2012a, Behroozi et al., 2019, Nagy, 2019, McDowell, 2015]. The introductory paragraph in Programming Interviews Exposed: Secrets To Landing Your Next Job says it best:

> *Landing a great programming job isn't a matter of luck; it's a matter of preparation. The programming interview process that most software firms use today is designed to determine whether you can actually code.*

It can be a grueling process, especially because the limitations imposed by the interview format make the process almost completely different from anything you experience in school or on the job. If you've never encountered it before, it can be quite a shock. Even great programmers who are inexperienced with programming interviews often struggle if they are unprepared for what they will face [Giguère et al., 2013, p. Introduction].

This quote epitomizes not only the challenges inherent in computing interviews, but also the preparation necessary to successfully obtain a job offer. Such expectations are not only unfair to students or employees looking to change positions or companies, but it also creates an unequal divide between those who can prepare, and those unable to commit such vast quantities of time due to restrictions of classes, family, or other obligations [Lara et al., 2019]. Technical interviews are accused of perpetuating practices which may further discourage minoritized populations, and utilizing these methods to evaluate candidates neglects their inherent bias [Behroozi et al., 2020b]. Moreover, such a format may require acquisition of knowledge that is not even relevant for the real-life tasks expected in the role [Gant, 2019b].

Rather than answering the types of questions which may be encountered on the job, technical interviews often involve coding puzzles or obscure scenarios that necessitate an aptitude for rapidly finding efficient and/or scalable algorithms and data structures [Behroozi et al., 2019]. In Behroozi et al.'s (2019) analysis of posts on Hacker News, a computing-focused social news website, even seasoned job candidates with years of prior experience struggled with the hiring process because they were asked to extemporaneously implement concepts they infrequently used. Furthermore, technical interviews have been criticized for advancing less qualified candidates to a position simply due to their "individual characteristics" [Wyrich et al., 2019, p. 2] which make them more adept at solving questions in the desired format [Gant, 2019a]. Scholars caution that companies should be mindful of the limitations of using coding challenges when hiring, and how they may impact "personality diversity" [Wyrich et al., 2019, p. 30], which has been linked to building more effective teams [Cruz et al., 2015].

1.3 Motivation

Dissertation statement: *The hiring process in computing is largely under-explored; even more so when considering the implications on underrepresented groups in the field.*

Although the hiring process has previously been described as flawed or "leaky" [Ford et al., 2017a, Behroozi et al., 2020a], empirical evidence is needed to determine what hiring entails, and its impact on minoritized students. Current literature on the process does not provide a nuanced level of detail into the variation of students' experiences with preparation and job attainment. The goal of this dissertation is to define the hiring process, and to examine its impact on students, and their experiences. In particular, this work seeks to explore the pathways of women, Black/African American and Hispanic/Latinx students to job attainment, and to demonstrate the importance of not treating all students as a monolith.

1.4 Research Questions

To understand the hiring process in computing and its impact on diverse populations of students, I sought to answer the following research questions (RQs):

- **RQ1:** What does the hiring process in computing look like from both the applicant and industry perspective?

- **RQ2:** How do cultural experiences impact technical interview preparation?
- **RQ3:** How do technical interviews, and other professional and cultural experiences impact computing identity?
- **RQ4:** How do students describe their experiences with the hiring process in computing?

1.5 Methods Employed

While I will describe each method further in the subsequent chapters, broadly, the following methods were applied to address the RQs. First, I conducted a systematic literature review (SLR) to identify the present state of the art, and to formalize the process for hiring in computing from the perspectives of job seekers and industry (RQ1). Then, I employed an explanatory sequential mixed methods approach (RQ2-4), that applied both quantitative and qualitative techniques, to better understand student experiences with the hiring process, as shown in Figure 1.3.

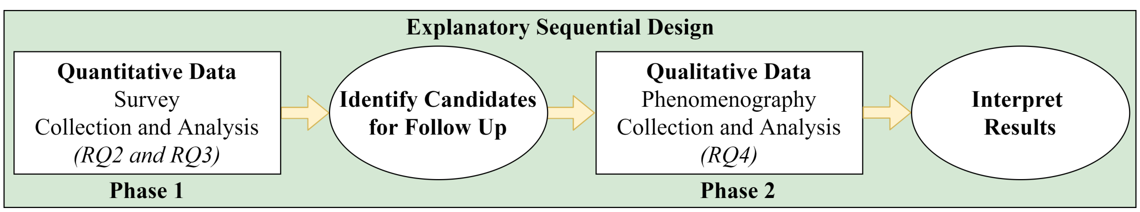


Figure 1.3: Explanatory sequential design employed in dissertation, adapted from [Creswell and Creswell, 2018]

In the first phase, quantitative data were collected via surveys of 740 undergraduate computing students at three universities on the number of interviews, job offers, and other self-reported measures of professional and cultural experiences, as well as demographics. The results were then analyzed using descriptive statistics, Wilcoxon rank-sum tests, and Kruskal-Wallis tests to examine students' interview preparation, and the role of cultural experiences (RQ2). Additionally, these data were analyzed using exploratory factor analysis, confirmatory factor analysis, and linear regression to evaluate students' experiences with the hiring process, as well as the impact of professional and cultural experiences on computing identity (RQ3). I further considered the interactions between these experiences and social identity for groups underrepresented in computing —women, Black/African American, and Hispanic/Latinx students. The results of the quantitative work were then used to inform the second, qualitative phase. I performed discursive phenomenography, using the findings from phase one to inform the selection of participants and questions asked, and to explore the results obtained in depth as I sought to establish an understanding of the phenomena (RQ4).

Although data for each phase were collected, assessed, and interpreted separately, explanatory sequential design is predicated on integration between the phases [Creswell and Creswell, 2018]. As such, it is common to provide the results of each, and then to discuss how the results in the second phase expand upon those obtained in the first, which this dissertation does in its final chapter. While the data from each phase cannot be directly compared, the strength in this methodology is that the initial results are understood in greater detail, through nuances in understanding and analyzing the experiences.

1.6 Outline of the Dissertation

This dissertation is structured as follows:

- *Chapter 2* reviews the theoretical frameworks applied in this dissertation, which served as a guide throughout the various research questions: Identity

Theory, Intersectionality, Community Cultural Wealth, and Social Cognitive Career Theory.

- *Chapter 3* discusses the systematic literature review (SLR) conducted to conceptualize and synthesize a general overview of the hiring process for computing fields. This chapter serves to answer RQ1 of the dissertation, presents the current state of the art on what the process entails, and examines how existing practices may create an additional barrier for females, Black/African American, and Hispanic/Latinx job applicants. The SLR presented is composed of three publications presently in press ([Lunn and Ross, 2021a], [Lunn and Ross, 2021b], and [Lunn and Ross, 2021c]).
- *Chapter 4* describes students' preparation practices for technical interviews, and highlights the cultural experiences that may impact job attainment for different populations of students, to answer RQ2 of the dissertation. The work presented is from a publication presently in press ([Lunn et al., 2021b]).
- *Chapter 5* addresses students' experiences with technical interviews, and other professional and cultural experiences, and their impact on computing identity, to answer RQ3. The study presented here, is from a publication presently in press ([Lunn et al., 2021a]).
- *Chapter 6* examines students perceptions of the hiring process, and their experiences with job attainment to answer RQ4. It also includes specific recommendations for students, educators and academia, and the computing industry to improve the hiring process, and preparation. I describe what challenges may further impact students of different races, ethnicities, and genders, and provide suggestions on how to improve diversification in the workforce.

- *Chapter 7* presents a summary of the studies conducted and their findings. Finally, this chapter wraps up with future directions for additional research, and concluding remarks.

Two additional publications are relevant to this work, [Lunn et al., 2020, Lunn et al., 2021c], and may be mentioned in the subsequent chapters, although they were beyond the scope of the RQs. It should be noted that throughout the document, the numbering of RQs within each chapter may vary from those for the compiled dissertation, and there may be some duplication in the description of the theoretical frameworks. This is to maintain the features of already published articles. Furthermore, this is my dissertation work, however, some collaborative papers were written with others, so there is a shift from "I" to "we" as well, over the course of the document. Finally, the definitions described throughout this dissertation can be accessed in the Appendix.

CHAPTER 2

THEORETICAL FRAMEWORKS

Theoretical frameworks are established paradigms used to provide context and structure to a research plan, to ground work in recognized theories, and to offer insight into the "factors most likely to have an effect" when considering situations where it is impossible to control for every variable [Borrego, 2007, p. 92]. Strong theoretical frameworks can "reveal existing predispositions" researchers may have about their inquiry and are considered advantageous throughout all phases of research — including planning, data collection, analysis, and its interpretation [Collins and Stockton, 2018, p. 1]. They inform the overall aims, construct research questions, identify limitations or threats to the validity, and emphasize the research's utility. It has been argued that employing theoretical frameworks, along with rigorous methods, can improve the quality of research, add strength to interpretation of the results, and can result in developing knowledge, understanding, and complex insights [Borrego, 2007, Collins and Stockton, 2018]. While researchers may struggle to select which framework is appropriate for their purposes, it is critical to bear in mind there may be multiple options which are applicable [Borrego, 2007]. However, depending on the goal and/or design of the work, some frameworks may be more suitable than others.

This dissertation intends to highlight the benefits of considering diverse accounts of the process of hiring in computing, to develop an understanding of the phenomenon. There are four frameworks which primarily guided the development and interpretation of this research: 1) Identity Theory; 2) Intersectionality; 3) Community Cultural Wealth (CCW); and 4) Social Cognitive Career Theory (SCCT). I first discuss identity theory in Section 2.1, broadly describing the conceptualization of identity, and then delve into more specific aspects relevant for this research, including social identity, disciplinary identity, and computing identity. Then I review intersectionality, and its impact on identity in Section 2.2. This work also draws on knowledge and understanding within the community, and considers the capital that individuals offer to computing, as well as how their own identities contribute to their cultural and professional experiences and job attainment. To achieve this, I have selected the community cultural wealth model, which I cover further in Section 2.3. Then, I detail social cognitive career theory and the factors influencing interview preparation and job attainment in Section 2.4. Finally, I summarize how these frameworks converge to benefit this dissertation in Section 2.5. Some of the descriptions of the frameworks presented in this chapter are part of the published works [Lunn et al., 2021a, Lunn et al., 2021c, Lunn and Ross, 2021b].

2.1 Identity Theory

2.1.1 Background

Identity is considered a complex, context-dependent, and ever fluctuating conceptualization that is rooted in a person's position individually and as a member of different groups [Gee, 2000, Li, 2009, Spears, 2011]. Gee's theory of multiple identities (2000) describes the ways that individuals' varying aspects of identity, being recognized as a particular "kind of person" connects to their societal performance [Gee, 2000, p. 99]. It describes that although components of identity may be formed and persist uniquely, taken together, they are not discrete but interrelated. These aspects of identity are shaped by interactions, and while they may exist in particular contexts (e.g., being a "activist") or moments in time (being an "undergraduate student"), they also can influence each other (e.g., an undergraduate student that launches a protest against their university). Such varied traits and positions may shape motivation, actions, and perceptions of an individual by themselves and others [Oyserman and Destin, 2010] and may also require negotiating amongst diverse, and often conflicting, sources (e.g., the way peers may view the student protesting compared to an administrator of the university) [Gee, 2000].

While identity is focused on the individual, socio-constructivist scholars argue that it is constructed within structures or communities [Sarbin and Kitsuse, 1994]. This perspective places further emphasis on the interpersonal relationships and social interactions. According to this view, encounters with others are what define and reify identity [Burr, 2006]. Lave and Wenger also highlight the importance of a social community and describe how active participation is established and reinforced through an individual's experiences [Lave et al., 1991, Wenger, 1999]. In computing, this has been shown to be mediated through interactions with others, such as friends and family, professors, and mentors [Peters et al., 2014]. This is particularly relevant to this dissertation, where I explore how different cultural experiences may contribute to an individual's disciplinary identity. It should be noted that identity is a broad terminology that encompasses multiple forms. In this work, I primarily focus on social and disciplinary identity, specifically computing identity, as shown in Figure 2.1.

2.1.2 Social Identity

Social identity has been previously defined as a type of identity that evolves in relation to societal interaction, communication, groups, and constructed categorizations of attributes and characteristics [Tajfel et al., 1979, Goar, 2007, Bliuc et al., 2011, Johansson, 2015]. It has been described in terms of the ways that an

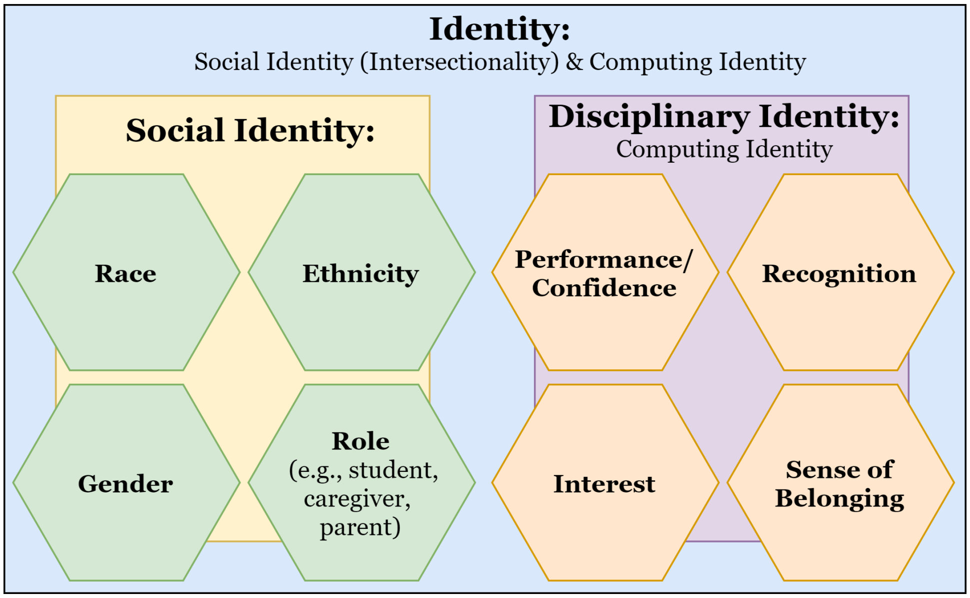


Figure 2.1: Identity overview

individual's identity is connected to larger collective identities [Johansson, 2015]. Conceptually, individuals may self-assign themselves to a particular group based on their social environment. However, labels and categories described by social identities, such as "race," "ethnicity," and "class," are constructed by society and are ascribed to a person, not biologically based [Johnson, 2013, Omi and Winant, 2014]. Although social identification within a particular group may result in an enhanced sense of unity and cohesion, these "attachments" have also historically lead to inter-group conflicts, injustice, and discrimination [Tajfel et al., 1979, Abrams and Hogg, 2006, Omi and Winant, 2014]. Since social identity can encompass so many different aspects of identity, I want to make explicit that in this research the focus is on the constructs of race, ethnicity, gender, and role.

Since race, ethnicity, and culture are often used interchangeably, and the precise definitions are often debated, I want to clarify the use of the terms. Race is a concept which psychologists note can pose some difficulty to discuss. Although typically race has been described by physical features like skin color, or facial proportions and features, psychologists caution that these are treated as features belonging to geographically isolated groups. Yet, in a diverse world in which populations do not subscribe to maintaining genetically pure populations, such classifications can be ambiguous [Jones, 1991]. Furthermore, an individual may identify with more than one race. More recently, rather than focusing on biological or physical features, *race* has been "redefined as a cultural and socio-political construct" [p. 68][Dein, 2006]. Omi and Winant have described how "race and racism remain unstable, contested, and ubiquitous, at both the experiential or 'micro-' level and the structural or 'macro-' level of U.S. society" [Omi and Winant, 2014, p. 246]. However, such socially constructed labels are still commonly used, and typical categorizations for race according to the United States Census Bureau include [U.S. Census Bureau, 2019]: White, Black or African American, Asian, American Indian or Alaska Native, or Native Hawaiian or Other Pacific Islander. In this research, race is acknowledged to be a social construct, although participants are asked to self-identify with as many categorizations as they feel are applicable using the labels previously described by the U.S. Census Bureau.

The term *ethnicity* is typically used to denote groups which share "a common nationality, culture, or language" [Betancourt and López, 1993]. Ethnicity and culture have been described as sharing a symbiotic relationship, in which cultural background can correspond to ethnic affiliation, but likewise, being a member of an ethnic group may contribute to culture. As such, Betancourt and López emphasize that "ethnicity becomes a means by which culture is transmitted" [Betancourt and López, 1993, p. 631]. Fredrik Barth, a socio-anthropologist, described a relational theory of ethnicity whereby importance is placed on between-groups differences rather than the cultural contents of a particular group [Barth, 1998, Barth, 1969]. He brought attention to the notion that ethnicity is more about the interaction process that exists between groups, rather than a static entity. Thus, a person's ethnic identity is not just about a set of features, but rather is constructed, reified, and altered based on interactions. According to the U.S. Bureau of Labor Statistics, those who identify as Hispanic, Latinx, or Spanish origin can select this as their ethnicity [U.S. Bureau of Labor Statistics, 2018], although they may have one or more distinct race designations as well. The work that follows in this dissertation will again use the labels defined by the U.S. Census Bureau, allowing students to self-select their ethnic identity as applicable.

Meanwhile, culture is a concept which is often linked with the notions of race, ethnicity, and social class [Betancourt and López, 1993], although cultural psychologists have debated its exact definition for quite some time [Brislin, 1973]. One of the prevailing psychological descriptions for culture, denoted by Triandis [Triandis, 1980] considers *culture* to be defined by subjective facets such as the social norms, roles, beliefs, and values. These elements span a number of areas such as roles within families, patterns for communication, and even affective styles. Hofstede [Hofstede, 1991] approached culture as a type of psychological software, a "software of the mind" since, like code on a computer's operating system, it provides an inherent way of approaching and understanding others and making sense of the world. Later versions by Hofstede et al. describe this type of psychological programming for culture as being divisible by six dimensions [Hofstede et al., 2010]: power distance, individualism versus collectivism, masculinity versus femininity, avoidance of uncertainty, long- or short-term orientation, permissiveness versus austerity. Comparatively, Faure and Rubin describe culture as a type of collective meanings, beliefs, and values that shape national or ethnic groups and guide their behaviors [Faure and Rubin, 1993]. Therefore, although ethnicity and culture are separate concepts, they often intertwine as well. In this research, culture will be examined in terms of the cultural experiences (e.g., caring for a family member, working a job) that may impact students' computing identities and which can affect their ability to prepare for technical interviews.

While an individual's roles (such as being a student, parent, or caregiver) may be variable over time, *role identity* develops along with personal identity, and shapes how individuals perceive themselves in the present and future (e.g., as an engineer) [Paul et al., 2020]. As such, it is linked with disciplinary identity, and its development has been shown to have a strong impact on self-conceptions, engagement, and persistence [Callero, 1985, Verdín et al., 2018, Paul et al., 2020]. Role identity can be beneficial to recruitment and retention in STEM fields. However, identity scholars have cautioned that structural influences and competing identities can also pose a challenge to identity development for minoritized populations, who may have to navigate through systems which may have been historically dominated by White males [Rodriguez et al., 2019, Ross et al., 2021]. To this end, scholars have stressed the importance of considering the needs of diverse populations and intersectionality [Ross et al., 2017, Ross et al., 2020].

2.1.3 Disciplinary Identity

Disciplinary identity is described as an individual's identification with a domain and its affiliated community [Hazari et al., 2010, Taheri et al., 2018, Taheri et al., 2019]. Disciplinary identity frameworks emphasize taking account of students' ability to understand, perform, and find fulfillment in their discipline [Carlone, 2017]. In STEM fields, disciplinary identity theory has previously been demonstrated to be a valid and effective way of understanding and predicting persistence and career choice [Smith et al., 2005, Carlone and Johnson, 2007, Hazari et al., 2010, Cobb and Hodge, 2010, Cass et al., 2011, Cribbs et al., 2015, Hazari et al., 2015, Godwin et al., 2016, Dou et al., 2019]. It has also been noted by Li that, just like an individual's identification with a particular ethnic group, social psychological factors influence disciplinary identity [Li, 2009]. Prior work has also examined how learning experiences drive disciplinary identity development and the importance of studying disciplinary identity in order to address equity issues [Bell et al., 2017]. Previously, Hazari et al. [Hazari et al., 2020] have argued that rather than focusing solely on the comparison of underrepresented populations (e.g., women) to those considered "normative" in a field (e.g., men), it is vital to explore the experiences of marginalized populations by themselves.

2.1.4 Computing Identity

Computing identity, a type of disciplinary identity, is an expansion of the science identity work by Carlone and Johnson [Carlone and Johnson, 2007], and has been previously defined by the sub-constructs of sense of belonging, recognition, performance/competence, and interest [Taheri et al., 2018]. *Interest* is defined by a student's personal engagement with respect to computing, and includes possessing a passion for studying, practicing, and thinking about computing topics [Taheri et al., 2019, Mahadeo et al., 2020]. *Sense of belonging* is described as a student's feelings of belonging to a community or group related to computing [Taheri et al., 2018]. Meanwhile, *competence/performance* refers to the self-confidence a student has in their ability to understand computing topics, and their feelings of accomplishment towards the subject. *Recognition* is defined as the feelings from others such as teachers, family members, and friends in their belief in the student's abilities and knowledge on the topic [Taheri et al., 2019, Mahadeo et al., 2020]. Despite the fact that these sub-constructs are unique and independent, they may have components of convergence and can influence each other as well, and computing identity has been used as a model for computing choices and behaviors [Taheri et al., 2018].

While computing identity has been clearly defined in prior work, its attainment is not always straightforward. With the growth in technology access and usage, students have become increasingly familiar with computing and computers. However, this increase does not necessarily translate linearly into rising computing identities. For example, individuals who regularly use social media, with a larger proportion of women engaging in these activities than men, do not automatically develop computing identities [Goswami and Dutta, 2015, Wong, 2016]. In addition, previous work with African American males has demonstrated that just because students may have a passion for computer-related activities (e.g., gaming), this does not always equate to an interest in learning about computing, nor to the development of computing identity [DiSalvo et al., 2011]. Therefore, computing identity appears to be the coalescence of several convergent factors and highly influenced by social perceptions of computing identities [Wong, 2016].

2.1.5 Application

Social identity played an important part in answering each RQ. Given that this work sought to understand the impact of race, gender, ethnicity, and role (e.g., as a student or parent), it was a vital consideration throughout the process — planning and design, data collection, analysis, and interpretation (which will be described further later) of all subsequent chapters. Meanwhile, understanding students' role identity in relation to a discipline (their disciplinary identity), and specifically computing identity, was applied when answering RQ3 and RQ4 as described:

- **RQ3 (Chapter 5)**: RQ3 focused specifically on how technical interviews, and other professional and cultural experiences impacted computing identity. Therefore, social identity theory (including the constructs of race, gender, and ethnicity), and computing identity were used during the planning and design, data analysis, and interpretation phases. In the planning phase, they guided the development of the research questions, giving consideration to the impact of diverse social identities and how experiences may differentially contribute to students' computing identities. In addition, they drove the design of survey, influencing the questions asked, such as demographics and items previously validated that were used to define the latent variables for the sub-constructs of computing identity [Taheri et al., 2018, Taheri et al., 2019]. They also contributed to the choice of analytical assessments (e.g., Wilcoxon rank-sum tests for comparisons, and regression interaction analyses using computing identity as the dependent variable). Furthermore, distinct social identification played an important role in understanding the salient professional and cultural experiences, particularly for groups underrepresented in computing. Finally, they drove the interpretation of the findings as social identity situated the unique experiences reported and their contributions to computing identity.
- **RQ4 (Chapter 6)**: RQ4 sought to understand students' perceptions of their experiences with the hiring process, and its application was limited to data collection (in terms of defining the interview protocol), and the interpretation of the results.

2.2 Intersectionality

2.2.1 Background

Enmeshed within the concept of social identity is a related but unique concept described as intersectionality. *Intersectionality* refers to a theoretical framework for exploring the overlapping components of an individual's identities— whether political (e.g., political affiliations), social (e.g., race, gender, disability), organizational (e.g., job title), or circumstantial (e.g., student, parent) [Corlett and Mavin, 2014]. This framework argues that men and women are not a monolith [Beddoes and Borrego, 2011, Collins and Bilge, 2016, Lord et al., 2009], and describes how "power relations influence social relations across diverse societies as well as individual experiences in everyday life" [Collins and Bilge, 2020, p. 1].

Intersectionality presents the opportunity and the argument for disaggregating data and evaluating, Black men and women, Hispanic/Latinx men and women, Indigenous men and women, and Asian men and women, and their complex identities, rather than lose them in overgeneralized, aggregated data [Lunn et al., 2021c, Ross et al., 2020]. This theory is particularly pertinent when examining marginalized populations, given that it encourages exploration of the subtleties and experiences of those who may straddle multiple axes of oppression, such as racism, sexism, xenophonia, ableism [Crenshaw, 1989, Delgado and Stefancic, 2001, Corlett and Mavin, 2014, Collins and Bilge, 2020]. It is also important for learning about what motivates perseverance and assessing which pedagogical methods work best for different students [Charleston et al., 2014, Hodari et al., 2014, Hodari et al., 2016, Ross et al., 2020], since it cannot be assumed that broad suggestions to improve understanding, persistence, or retention, for the general population are necessarily applicable or helpful for underrepresented populations [Tsui, 2007].

Many studies which fail to disaggregate by race and gender neglect the experiences of women of color, referring to those women that identify as Black/African American, Hispanic/Latina, Native American, Asian, or mixed race/ethnicity [Ong et al., 2011, Hodari et al., 2016, Ong et al., 2018]. Previously, literature has described how women of color are shaped by existing within multiple spheres of minority categorization, and the importance of considering intersectional identity as more than just the sum of individual labels [Crenshaw, 1990]. Prior work by scholars interested in the nuance associated with calling attention to, investigating, and understanding the experiences of women at the intersection of race and gender have provided the precedent for continuing this line of inquiry [Ong et al., 2011, Varma, 2007a, Varma, 2010, Trauth et al., 2012, Ross et al., 2020, Rankin and Thomas, 2020, Lord et al., 2009]. Intersectionality has also been demonstrated to play an important role in computing fields, particularly in considering how stereotypes and encounters may impact individuals [Trauth et al., 2012, Ross et al., 2020]. For example, Trauth et al. observed that minority males (specifically Black/African Americans and Hispanic/Latinx males) and White females tend to be subject to "masculine stereotyping" for IT skills. It was noted that although all females may have faced sexist treatment, White women may still receive different treatment as a result of "ethnic privilege." Accordingly, Black and Hispanic women have distinctive identities, shaped by historic discrimination. African American women in computing often feel isolated, and it is necessary to create a welcoming environment that fights against oppressive practices and implicit bias [Charleston et al., 2014]. Likewise, Latina students in STEM disciplines also reported feeling marginalized and isolated [Rodriguez and Blaney, 2020].

Research focused on the intersectionality of Black females by Solomon et al. illustrated that many studies on sense of belonging in computing tend to focus solely on notions of Black masculinity or White femininity [Solomon et al., 2018]. However, Solomon et al. argue that Black females have their own cultural strength and resilience, resulting from a need to assert themselves and gain visibility, to survive. They are not always given the same "systematic protections as other girls or Black men" [Solomon et al., 2018, p. 4]. Therefore, building a community for women of color, and providing social support could be beneficial for learning outcomes [Hodari et al., 2014]. Furthermore, it has been suggested that offering same-race or gender role models and faculty could inspire, reinforce a sense of belonging, and also ameliorate the climate in otherwise inhospitable educational settings, serving as a counterspace for minoritized populations in STEM disciplines [Charleston et al., 2014, Ong et al., 2018, Rodriguez and Blaney, 2020].

The term *counterspaces* refers to

> academic and social safe spaces that allow underrepresented students to: promote their own learning wherein their experiences are validated and viewed as critical knowledge; vent frustrations by sharing stories of isolation, microaggressions, and/or overt discrimination; and challenge deficit notions of people of color (and other marginalized groups) and establish and maintain a positive collegiate racial climate for themselves" [Ong et al., 2018, p. 209].

In STEM fields, counterspaces such as formal and informal groups, organizations, and activities (such as diversity conferences) have been demonstrated to provide opportunities to develop a cultural community and social identity, and to enhance learning [Ong et al., 2018, King and Pringle, 2019]. Moreover, counterspaces have been shown to provide emotional support and strategies to combat the exclusion faced in fields that are often White and male-dominant such as computing [Ong et al., 2018, U.S. Bureau of Labor Statistics, 2021a]. This research focuses specifically on the intersectionality of race, gender, and ethnicity, and uses this theory to explore students' pathways to a career, as well as what counterspaces on which they may rely.

2.2.2 Application

In this dissertation, intersectionality was used to answer RQ1 and RQ4:

- **RQ1 (Chapter 3)**: RQ1 employed a SLR to examine the hiring process, and mentions of inclusivity or attempts to improve diversity. Intersectionality was applied during interpretation of some of the publications to critically examine existing work and its attention to intersectional identities, as discussed within the context of hiring and the computing workplace.
- **RQ4 (Chapter 6)**: Intersectionality played a vital role in the phenomenographic inquiry of RQ4. In this chapter, I endeavored to understand the distinct experiences of men and women from different racial/ethnic backgrounds. Intersectionality played a role in the participants chosen, as I sought equal numbers of students that identified as men and women, and particularly, sought to emphasize the selection of men and women that identified as Black/African American and/or Hispanic/Latinx to ensure diverse representation and understanding of the phenomena and their intersectional identities. It also shaped the questions asked, and influenced the addition of prompts about the diversity at companies (e.g., "Did you notice that the staff and/or interviewers were female? Black or African American? Etc.) and students' perceptions of inclusivity in the field. Due to the nature of the qualitative methodology chosen, it was not involved with the analysis phase (since the categories are meant to emerge from the data itself without the influence of

a theoretical framework). Furthermore, intersectionality was beneficial during the interpretation of the results (represented as an outcome space), for unpacking students' pathways to a career, and the challenges and discrimination they encountered.

2.3 Community Cultural Wealth (CCW)

2.3.1 Background

CCW is derived from work by Solórzano, Villalpando, and Oseguera [Sólorzano et al., 2005], which drew on critical race theory to discuss the "cultural wealth" (or assets) marginalized populations may leverage to overcome oppressive practices and/or barriers. The goal of their efforts was to counter deficit-based stereotypes, assumptions, expectations, and perpetuation of such methods of inquiry. Yosso further expanded the concept, outlining six different types of capital that exist for people of color to promote success [Yosso, 2005], as shown in Figure 2.2.

Specifically, the six types of capital include:

1. *Resistant capital:* Seeking social justice through knowledge, skills, and behaviors which "challenge the status quo" [Solórzano and Villalpando, 1998, p. 81].

2. *Familial capital:* Knowledge, skills, support, and resources gained through immediate and extended family, which can serve to reduce isolation and establish connections to the community. Moreover, they can "model lessons of caring, coping and providing (educación), which inform our emotional, moral, educational and occupational consciousness" [Yosso, 2005, p. 79]. Previously

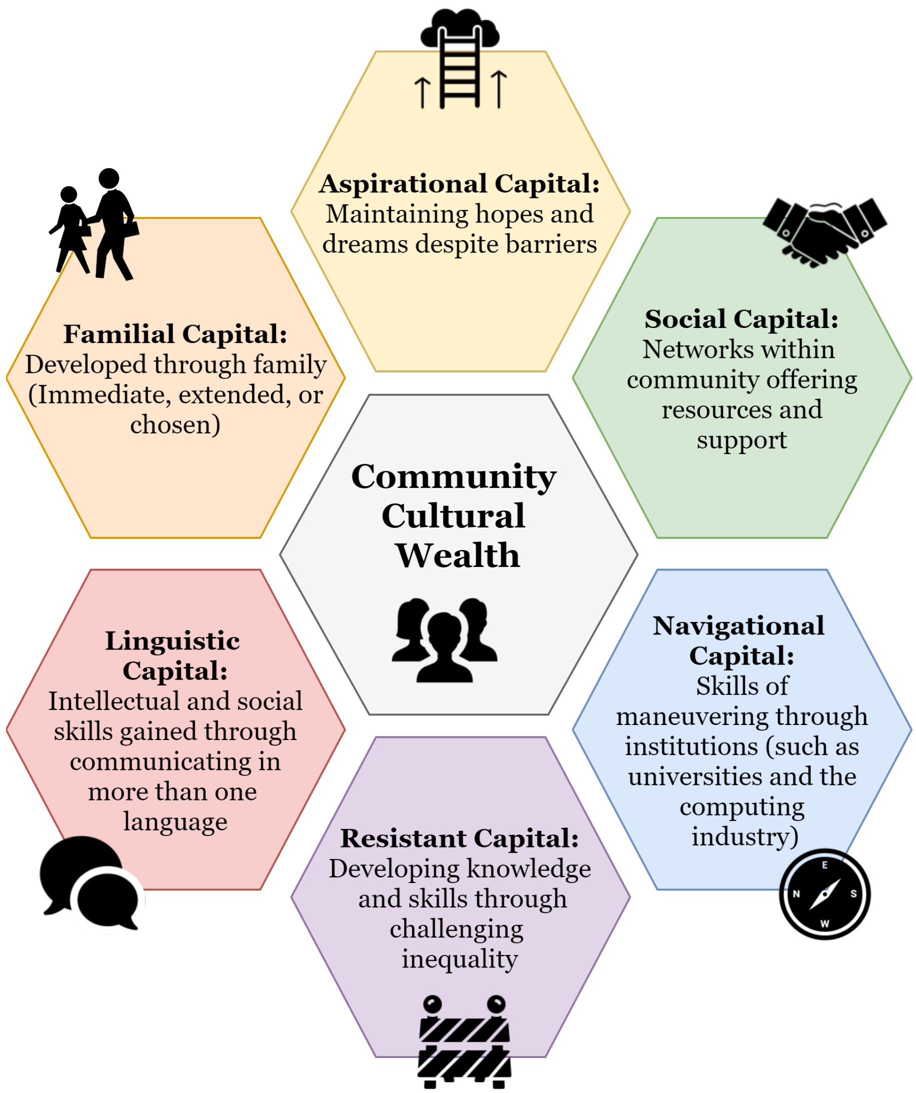


Figure 2.2: Community cultural wealth model (©2021 IEEE from [Lunn and Ross, 2021b])

Denton and Borrego have mentioned this may also include "campus communities that serve as an extended family" [Denton and Borrego, 2021, p. 66].

3. *Aspirational capital:* Maintaining a positive outlook for future achievement and success despite real and perceived challenges.

4. *Social capital:* Networks of people and community resources, e.g., peers.

5. *Navigational capital:* Adaptive strengths called upon to maneuver through social institutions, while acknowledging "individual agency within institutional constraints, but it also connects to social networks that facilitate community navigation through places and spaces including schools, the job market and the health care and judicial systems" [Yosso, 2005, p. 80].

6. *Linguistic capital:* Intellectual and social skills attained through communication experiences in more than one language and/or style.

CCW can be a powerful mechanism for increasing student engagement, persistence, interest, and for skill development [Burt and Johnson, 2018, Denton et al., 2020, Rincón and Rodriguez, 2020, Ong et al., 2020, Lane and Id-Deen, 2020, Butler et al., 2020]. Faculty that encourage students to take advantage of their office hours to offer professional and academic advising, promoting internship and research, and other forms of social support, can strengthen the social capital that establishes "supportive family-like relationships." This tends to also touch on familial capital, and may also provide a form of navigational capital, as the advising helps students to maneuver through their university. Additionally, instructors should apply an asset-based approach, like CCW, when considering the projects and examples that they give to students, to help foster additional capital.

CCW is also considered effective tool for describing benefits of external contributors and extracurricular support systems to empower minoritized populations

[Rincón and Rodriguez, 2020, Liou et al., 2009]. For example, peer support leverages aspirational capital and help minoritized populations "[...]to see themselves as STEM-engaged individuals and persist towards STEM careers" [Rincón and Rodriguez, 2020, p. 6]. Peer support can also tap into social capital, as students build a community and work together to study and to solve problems [Lane and Id-Deen, 2020].

2.3.2 Application

Applying CCW as the theoretical underpinnings of this research, I examined how identity, experiences, social relationships, and interests contributed to CCW, and in turn, how CCW contributed to academic persistence and career achievement in computing [Yosso, 2005, Samuelson and Litzler, 2016]. Listening to the experiences that students had with the hiring process in computing, I explored how they drew on their own inherent capital, as described by the CCW model, to navigate through technical interviews. Since success in computing requires a mix of hard and soft skills [Gallagher et al., 2011, Litecky et al., 2012, Ahmed et al., 2012, Ahmed et al., 2013, Heffernan, 2014, Calitz et al., 2014, Sarma et al., 2016, Ibezim; Ekpereka, 2017, Watson et al., 2017, Florea and Stray, 2018, Florea and Stray, 2019, Burke et al., 2018, Scaffidi, 2018a, Oguz and Oguz, 2019], I hoped to better understand where participants struggle, and where their unique backgrounds may serve to provide an advantage in different stages. For example, communication skills are considered extremely important to employers [Ahmed et al., 2013, Matturro, 2013, Radermacher et al., 2014, Sharma, 2014, Hiranrat and Harncharnchai, 2018, Ford et al., 2017a, Peslak et al., 2018, Dubey and Tiwari, 2020, Garousi et al., 2019c, Oguz and Oguz, 2019, Gurcan and Sevik, 2019]. As such, understanding the linguistic capital that a multi-lingual individual has, or that of a student who has previously served as an interpreter in their own family, may make them more adept at sharing their work and explaining their code during the hiring process [Ahmed et al., 2013, Trauth et al., 2012, Stevens and Norman, 2016]. Long term, this translates into a potential employee that can effectively communicate not only with their boss and coworkers, but also with clients when trying to elicit specifications for software. CCW was employed to answer RQ1, 2, and 4 in the following way:

- **RQ1 (Chapter 3)**: As part of the SLR, CCW was applied during interpretation of some of the publications selected for review, particularly in the context of providing recommendations for ways to leverage cultural wealth during students' time in school, throughout the hiring process, and in the workplace.
- **RQ2 (Chapter 4)**: RQ2 obtained quantitative findings on students' preparation and job attainment, and all forms of capital described by the CCW model were used during interpretation of the results.
- **RQ4 (Chapter 6)**: CCW was used throughout the process of RQ4, during planning and design, data collection (in terms of defining the interview protocol), and interpretation of the results. All forms of capital described by the model were considered when preparing the questions, and in interpreting the outcome spaces that resulted from the inquiry.

2.4 Social Cognitive Career Theory (SCCT)

2.4.1 Background

Social Cognitive Career Theory is often used to understand the intrinsic and extrinsic variables that influence an individual's occupational choices and performance

[Lent et al., 1994, Lent et al., 1999, Lent et al., 2002, Lent et al., 2011]. Applying Bandura's general social cognitive theory as the foundation [Bandura, 1986], SCCT considers self-efficacy, outcome expectations, and personal goals as central facets of the framework for disciplinary interest, vocational decisions, and career development [Lent et al., 2002, Lent et al., 2018]. An overview of the SCCT model is shown in Figure 2.3, as described by Lent, Brown, and Hackett [Lent et al., 1994].

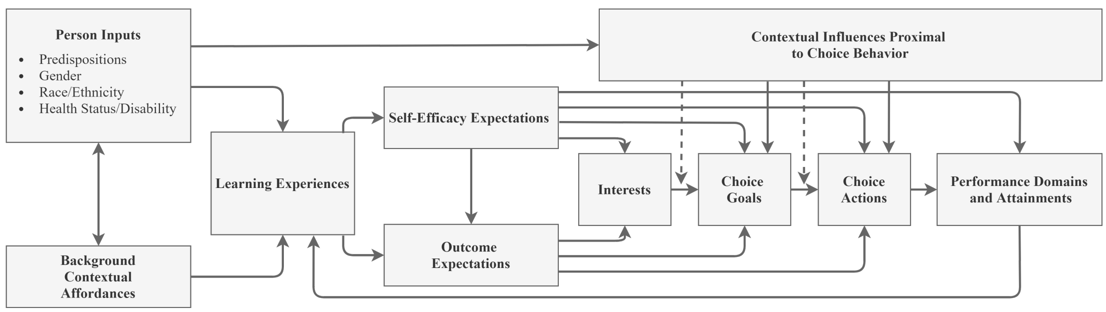


Figure 2.3: Overview of Lent, Brown, and Hackett's SCCT model, [Lent et al., 1994]

Self-efficacy refers to an individual's personal belief in their own capability of performing a particular task or behavior to elicit a desired outcome [Bandura, 1986]. Higher self-efficacy is linked to increased likelihood of developing an interest in the field, and to the pursuit of performance goals [Bean and Eaton, 2000, Carrico and Tendhar, 2012]. 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 [Fouad and Santana, 2017, Lent et al., 2018]. Furthermore, the SCCT model has also been shown to account for engagement, interest, and persistence specifically in computing fields, and it was demonstrated these effects were moderated by gender, race, and ethnicity [Lent et al., 2008, Luse et al., 2014, Alshahrani et al., 2018].

While the use of SCCT in this work will be limited to specific components relevant to interview preparation (described further in Chapter 4), the link between SCCT and disciplinary identity should also be acknowledged. SCCT explains an individual's background, their educational experiences, interest, self-efficacy, persistence, and actions towards attaining a career. Similarly, disciplinary identity theory describes how students' feelings of competence/performance, recognition, interest, and sense of belonging contribute to form their identity [Carlone and Johnson, 2007, Hazari et al., 2010].

2.4.2 Application

I applied SCCT to answer **RQ2 (described in Chapter 4)**, to explore how gender, race, and ethnicity impact contextual influences proximal to choice behavior, to affect the actions of technical interview preparation, and ultimately job attainment in computing. While I presented descriptive statistics for all students to offer a broader look at students' technical interview quantity, preparation, and outcomes, I also considered how specific underrepresented groups (e.g., women, Black/African American students, and Hispanic/Latinx students) were impacted. I focused 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.

2.5 Conclusions

Taken together, the chosen frameworks each contributed vital aspects to the conceptualization and understanding of students' experiences in computing and the hiring process. SCCT touches on the impact of person inputs, such as those described by social identity theory, on contextual influences (e.g., cultural and professional experiences). Furthermore, it emphasizes how these can affect choices and actions, such as interview preparation, to attain a job offer.

Social identity theory and intersectionality are valuable theoretical frameworks when considering the unique experiences and complexities inherent for students' straddling diverse categorizations of race, ethnicity, gender, and roles. Exploring students' pathways into the field, particularly those of women, Black/African American, and Hispanic/Latinx students, is useful for appreciating what encouraged persistence and development of computing identity, feeling like a "computing person." Such information is beneficial to creating more inclusive practices in classrooms and in the workplace, and in establishing a more equitable hiring process, to foster diversity in personnel and thinking. CCW also highlights the capital minoritized students leverage to attain a position in computing, and served as an ally in highlighting the positive traits and supports that can be called upon to succeed. This research fills a gap in the literature to not only provide empirical evidence of what hiring in computing entails and students' experiences, but in particular, to provide insight into how hiring impacts a range of students.

CHAPTER 3

HIRING PROCESS IN COMPUTING

Given the paucity of rigorous research surrounding the hiring process in computing, the motivation for this chapter (and RQ1 in the dissertation) was to create a comprehensive description of the hiring process from the perspectives of the employer/industry, and the job seeker. A systematic literature review was conducted to identify and classify the stages involved, and to learn about what traits and skills employers sought. Furthermore, publications were examined for attempts to make the process more inclusive, and to explore how existing practices may create additional barriers for female, Black/African American, and Hispanic/Latinx job applicants.

In this SLR, hiring was investigated throughout "computing fields" to account for ambiguity surrounding specific titles/roles. Furthermore, since the positions may exist in the U.S. or abroad as part of multinational or international companies, and scholars collaborating on research about hiring may span multiple continents, this work considered any publication written in English that described computing jobs around the world. Often the labels for different positions vary, so computing literature was included as defined by global descriptors: software engineering (SE), computer science, information technology, information systems (IS), computer engineering, or information and communication technology (ICT). This chapter includes an overview of the review protocl, the research questions, the criteria for inclusion and exclusion of literature, the publications identified, and the analysis of these works. The SLR presented is composed of three publications presently in press ([Lunn and Ross, 2021a], [Lunn and Ross, 2021b], and [Lunn and Ross, 2021c]).

3.1 Introduction

Obtaining a position in computing requires job seekers to demonstrate a range of competencies, knowledge, and abilities. Not only are they required to possess technical prowess, but also to have a good personality, a propensity for critical thinking, an aptitude for learning, and strong written and oral communication capabilities [Litecky et al., 2012, Florea and Stray, 2019, Scaffidi, 2018a, Oguz and Oguz, 2019]. To determine if a computing candidate possesses the necessary skills, companies often use technical interviews.

Currently, multiple papers review the hard and soft skills necessary for career success, [Ahmed et al., 2012, Singer et al., 2013, Ahmed et al., 2013, Heffernan, 2014, Tockey, 2015, Garousi et al., 2019b], which skills are knowledge deficiencies for recent graduates [Radermacher, 2012, Radermacher and Walia, 2013, Radermacher et al., 2014, Exter et al., 2018, Mardis et al., 2018, Penrod, 2019], and a few papers mention the hiring process broadly [Behroozi et al., 2019, Behroozi et al., 2020a, Behroozi et al., 2018]. However, more work is needed to describe what hiring in computing looks like, and what employers want from applicants. Furthermore, many reports and articles state that there is a diversity problem in computing, but rarely do these works examine how viable candidates are lost during the hiring process. Given that diverse students may have unique experiences and backgrounds that make them more adept in a number of areas salient for long-term success in computing, this investigation sought to understand what skills are valued during the hiring process, and which could be leveraged.

Before identifying biases in the hiring process, it is necessary to first gather the existing work on hiring practices in computing, and to explore mentions of attempts to increase diversity, or actions taken to make the process more inclusive.

To understand hiring, the skills preferred by employers, and considerations of equitable practices for all job applicants, this SLR considered several research questions. Given that each set of the research questions (RQs) were linked to a separate publication, all seven questions are presented for the three publications, labeled with the publication number and applicable RQ (using the convention P#RQ#):

Publication #1 [Lunn and Ross, 2021c] describes an overview of hiring process:

- **P1RQ1:** *What does the hiring process in computing entail for employers/industry?*
- **P1RQ2:** *What does the hiring process in computing entail for job seekers?*

Publication #2 [Lunn and Ross, 2021b] sought to understand what skills are valued during the hiring process, and which could be leveraged. Using the community cultural wealth model as a lens to explore the inherent capital that female, Black/African American, and Hispanic/Latinx students contribute, it answered:

- **P2RQ1:** *Which hard skills do employers assess during hiring for computing roles?*
- **P2RQ2:** *Which soft skills do employers assess during hiring for computing roles?*
- **P2RQ3:** *How could the hiring process be refined to better leverage community cultural wealth for groups underrepresented in computing?*

Publication #3 [Lunn and Ross, 2021a] sought to examine how workplace initiatives to broaden participation are applied during the hiring process itself, and attempts to make it more inclusive:

- **P3RQ1:** *What barriers exist for underrepresented groups during the hiring process in computing?*

- **P3RQ2:** *How have employers in computing tried to make the hiring process more inclusive for all job candidates?*

To address these questions, I took an inventory of present publications describing hard and soft skills for computing professions, and I also analyzed which skills are evaluated during the hiring process. Additionally, I discussed the importance of diversity in hiring, and offered suggestions on ways to make the process more inclusive. One of the main goals of this research is to raise awareness of the benefits of diversification of the workforce, and how approaches can be shifted to make hiring more inclusive. The community cultural wealth model and intersectionality were applied during interpretation of some of the publications to understand the unique experiences and findings on female, Black/African American, and Hispanic/Latinx students and workers, and the capital they contribute, as discussed within the context of hiring and the computing workplace.

3.2 Background

I first detail what hard and soft skills are in Section 3.2.1. I describe knowledge deficiencies further in section 3.2.2, and then, to provide background on the evolution of the computing interview process, discuss a brief history in section 3.2.3.

3.2.1 Hard versus Soft Skills

Hard skills are considered the skills that are specific for a particular "work setting," and are learned through education or during the time on a job [Ahmed et al., 2012]. Although the exact categories may vary, some examples include software engineering methods, business and entrepreneurship, relational versus non-relational databases, source code management, system administration, user interface design, and embedded, mobile, testing/quality, and web development [Scaffidi, 2018a]. Meanwhile, *soft skills* arise from an individual's personality, attitudes, behaviors, and ability to interpret social cues, to communicate, and to interact with others with emotional intelligence and empathy [Ahmed et al., 2012]. Some examples of soft skills include displaying an interest in learning, working cooperatively with others, possessing analytical skills, having strong communication skills, matching with the culture of the organization, being able to manage time effectively, and exhibiting an aptitude for troubleshooting or debugging [Heffernan, 2014, Stevens and Norman, 2016, Oguz and Oguz, 2019].

One of the more comprehensive skill categorizations identified was described by Calitz et al. for information and communications technology (ICT) positions. Their breakdown included necessary hard and soft skills requirements such as [Calitz et al., 2014]: problem-solving skills (e.g., creativity, research skills, logical thinking, and working under pressure), interpersonal skills (e.g., conflict resolution and teamwork), work ethic, language skills, business processes, management skills, internationalization skills, project management, strategy skills, business applications, current languages (such as .NET, Java/J2EE/J2P, C/C++, C#), legacy languages (such as Ada, COBOL, and Smalltalk), social network skills, software development, and mobile technologies.

3.2.2 Knowledge Deficiencies

Formal education has a disconnect with industry expectations [Radermacher and Walia, 2013, Oguz and Oguz, 2019]. A *knowledge deficiency* is defined as the disconnect between the capabilities, acumen, and understanding of recent graduates and the professional expectations held in the workforce [Radermacher and Walia, 2013]. Reports from both academia and industry are clear that a combination of hard and soft skills are needed to succeed in the field, and that many job applicants lack these abilities. Despite ongoing discussions and suggestions from both sides, neither side seems to arrive at a concrete way of better preparing applicants for hiring [Oguz and Oguz, 2019].

3.2.3 Evolution of the Programming Interview

Typically educational credentials are utilized as a way to measure the quality of participants [Christoforaki and Ipeirotis, 2015]. However, between the 1970s and 1990s the expectations for programmers changed and expanded. Not only were new hires expected to be technically proficient, but it was also assumed that they had an understanding of business, that they could demonstrate their ability to think critically, and that they could communicate effectively [Aken et al., 2010]. The way these skills were often assessed was through technical interviews.

Technical interviews are embedded into the larger hiring process for technology positions, and involve interviews in which the capability of those seeking a position are evaluated using live coding, logic, and problem solving [McDowell, 2015]. Over time, technical interviews have evolved to place an increased focus on analytical thinking, and have added increasingly challenging hurdles. Although a precise history and explanation for its evolution is murky, the origins of modern technical interviews dates back to hiring for a start-up during August of 1957 [Poundstone, 2003, Sello, 2012, O'Mara, 2019]. Rather than asking traditional questions related to programming, the founder of Shockley Semiconductor Laboratory, William Shockley, chose canonical questions that tested his candidate, James "Jim" Gibbons, on his critical thinking, analytical abilities, and problem-solving potential. A famous question included asking about the number of tennis matches needed to complete a singles tournament [Poundstone, 2003, Sello, 2012]. In addition, the responses to such questions were timed.

The rise of the internet in the late 1990s and early 2000s further contributed to changes in the hiring process [Gant, 2019a]. Initially, questions were developed in house, based on the needs of individual companies. This led to hiring managers asking more targeted questions that gave greater credence to real-world problems the applicant might encounter in their role. However, as technology continued to surge, between 2002-2008 the "in-house development quiz" lost traction. Instead hiring managers searched online for potential questions, operating under the assumption that candidates could similarly practice by preparing via material available online.

3.3 Theoretical Frameworks

Preliminary versions of the community cultural wealth (CCW) model were developed using critical race theory as a foundation by Sólorzano, Villalpando, an Oseguera [Sólorzano et al., 2005] to discuss the oppressive practices that may create barriers for marginalized groups and to counter deficit models. The concept was additionally developed by Yosso [Yosso, 2005] to further expand and define different types of capital that exist for people of color, as defined within their own community. Specifically, Aspirational, Linguistic, Familial, Social, Navigational, and Resistant forms of capital are combined to produce the CCW framework.

Previously, CCW has been demonstrated as an effective tool for considering the benefits of external contributors and extracurricular support systems to empower minoritized populations. In addition, work on students in STEM fields has shown it can also be a powerful approach for curricula development and teaching [Denton et al., 2020].

Meanwhile, intersectionality is a theoretical framework that considers the convergent components of identity and how they may contribute to discrimination and privilege [Corlett and Mavin, 2014, Rodriguez and Lehman, 2017]. As others have emphasized, neglecting intersectionality is attributed to overgeneralization, and/or a lack of understanding the nuances of specific experiences [Ross et al., 2020]. In this study, intersectionality was used to describe the work on men and women of color in the context of hiring and the workplace.

3.4 Methods

A systematic literature review (SLR) was conducted. A SLR is a methodical approach to gathering pertinent literature, assessing the content, and identifying gaps on a specific topic [Petticrew and Roberts, 2006]. The goal was to explore the existing literature, to identify, examine, and synthesize relevant work pertaining to diversity and inclusivity in computing [Petticrew and Roberts, 2006, Verdin et al., 2016]. This SLR was based on the guidelines proposed by Petticrew and Roberts (2006), and through application of the additional principles for SLR in software engineering described by Kitchenham and Charters [Kitchenham and Charters, 2007]. The research questions defined, inclusion/exclusion criteria established, and investigation were based off the PICOS (Population, Intervention, Comparison, Outcome, and Study Design) framework [Shaffril et al., 2020] described in Table 3.1.

PICOS Component	Study Consideration
Population	Job seekers, hiring managers, interviewers, employers, and employees of/for computing positions
Intervention	The hiring process in computing, with a focus on: • What do companies expect from job candidates • Barriers for underrepresented groups • Programs/initiatives established to broaden participation and to make the hiring process more inclusive
Comparison	Variations in the hiring process and programs/initiatives of different institutions, agencies, companies, organizations, businesses, associations, or firms
Outcome	Understanding of what has been done to improve diversity and to make hiring more equitable, and areas where improvement is needed
Study Design	Reviewing all empirical and analytical publications with a focus on the hiring process in computing fields, and programs/initiatives to broaden participation

Table 3.1: PICOS framework for structuring research questions and analysis

3.4.1 Source Selection and Search

Initially, a pilot search was conducted to identify the best search strings and databases to answer the RQs [Baker et al., 2020]. After refining the list, the final search was conducted in March and April of 2020. Specifically, I considered the areas pertaining to computing hiring, the skills needed for jobs, and attempts to make the process more inclusive as depicted in Figure 3.1.

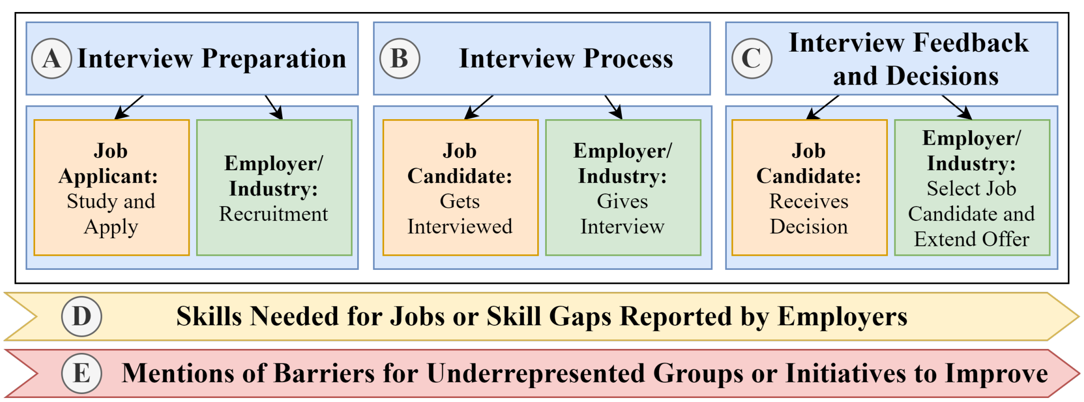


Figure 3.1: Overall hiring process with consideration of skills needed

As shown in this figure, I considered both the job applicant or candidate and the employer or industry perspectives. I looked into interview preparation (A), the interview process itself (B), and mentions of job feedback or offers (C). I also examined publications that mentioned interviews or hiring in reference to the desired skills of candidates (D). Additionally, I considered mentions of diversity issues in interviews or attempts to make the hiring process more inclusive (E).

Publications indexed in the following 4 databases were searched 1) Google Scholar (GS), 2) IEEE Xplore Digital Library, 3) ACM Digital Library, and 4) conference proceedings from ASEE. To keep the literature focused on the desired areas, search strings were created to query the selected sources. The following contained the relevant terms for the hiring process:

((Computing **OR** Technical **OR** Software Engineer* **OR** Software Develop*)
AND (Interviews **OR** Hiring **OR** Occupations **OR** Jobs))

OR

(Diversity **OR** Inclusivity) **AND** (Computing Interviews **OR** Technical Interviews **OR** Software Engineer* Interviews **OR** Software Develop* Interviews)

It should be noted that the asterisk (*) symbol in the list just described denotes a wildcard that broadens the search to consider words beginning with the same letters (using them as a prefix). For example, "Software Develop*" would find variations such as "Software Developer," "Software Developers," and "Software Development." Including this symbol in the database searches allowed for the consideration of as many relevant publications as possible from the stem word provided.

One issue encountered was the stopping conditions in the databases queried. For example, GS often lists hundreds of thousands of results. Due to the manual nature of the review process, it was not possible to analyze each result. However, I used the databases' internal ranking algorithms to restrict the number of results to the most relevant. This is consistent with the heuristics used by others conducting SLRs [Garousi et al., 2019b].

3.4.2 Study Inclusion and Exclusion Criteria

The search strings generated a lengthy list of sources, that often were not related to the research questions. To filter databases and publications from their title to abstract to content, I applied a list of additional criteria, illustrated in Table 3.2. Since computing fields are constantly in flux, and the hiring process has changed over time, it was necessary to limit the timeframe to publications between 2010 and 2020.

Inclusion	Exclusion
Publications that address the RQs	Publications not in English
Publications from 2010 or later	Publications from before 2010
Publications displaying empirical evidence	Publications based solely on personal opinions
Publications that clearly define their methods and sources and books where the author had experiences or credentials to validate their expertise	Publications without clear methods or books where the author's qualifications or credentials were not made explicit
Publications from journals, conference proceedings, books, or theses	Publications from corporate reports, blogs, patents, or opinion articles
Publications that discuss the hiring process in computing	Publications where computing fields are not the primary focus
Publications that discuss how to increase diversity or feelings of inclusivity in the hiring process	Publications that include diversity or inclusivity initiatives in a broad sense either during their education or in the workplace

Table 3.2: SLR inclusion and exclusion criteria

3.4.3 Study Execution

An overview of the SLR paper identification process is shown in Figure 3.2. After executing all search strings and manually searching through all selected sources, 6,890 publications were found. Then duplicates were removed, resulting in 5,640 publications. After applying the inclusion and exclusion criteria based on the title of those publications, 461 remained. The abstracts for these publications were read and also subjected to the same inclusion and exclusion criteria, leaving 237 publications. Each of the remaining publications was read in its entirety. After reading each of the selected publications, and applying the inclusion and exclusion criteria, only 64 remained.

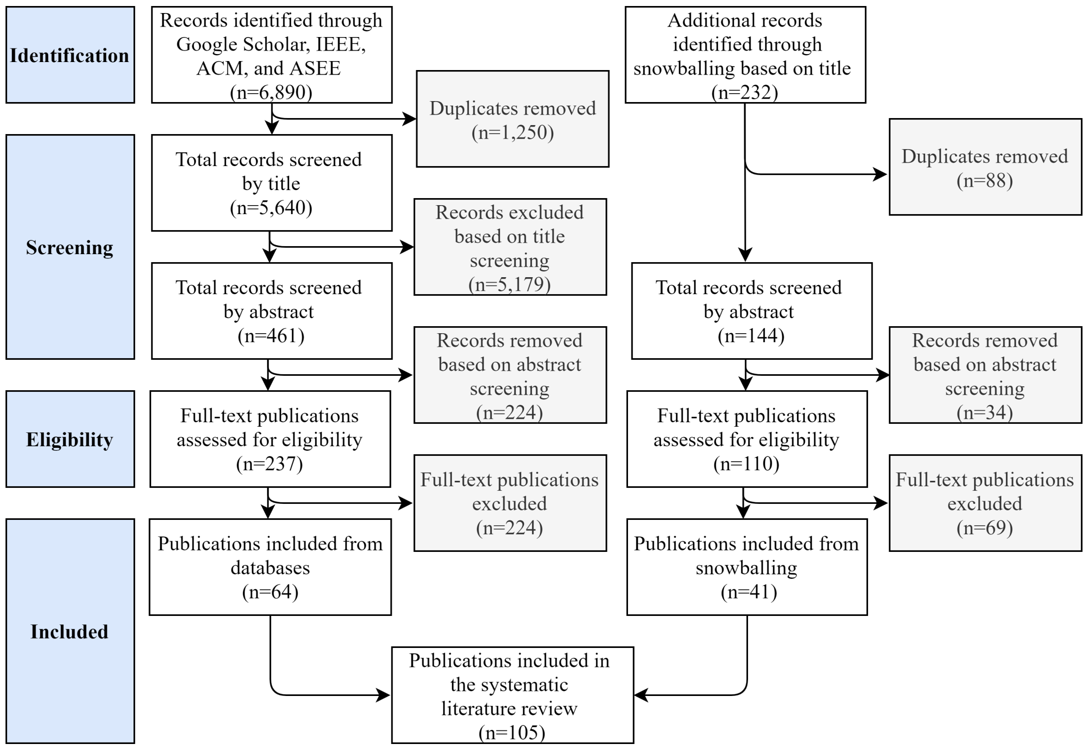


Figure 3.2: SLR paper selection process

I also applied forward and backward snowballing to maximize relevant sources as much as possible in the candidate pool [Wohlin, 2014]. Snowballing, for these purposes describes the use of the paper's reference list (backward snowballing) or the use of the citations referencing a paper, to identify additional relevant resources (forward). During this phase, I employed a process similar to that undertaken with publications selected in the database search, and applied the same inclusion and exclusion criteria. Three rounds of forward and backward snowballing identified

232 potential candidates, based on their titles. Snowballing was conducted until the no new sources were obtained. After duplicates were removed, 144 publications remained, and the abstracts were read from each of these. Then, 110 publications were selected to read the full publications. 41 additional publications were identified from snowballing. This resulted in a total final total of 105 publications included in the systematic literature review.

3.5 Results

First I describe the publications identified in Section 3.5.1. Then, I discuss digital and non-digital sources in computing salient for hiring and interview preparation in Section 3.5.2. Next, I review the hiring process in computing in greater detail, and consider the perspective of the employer/industry in Section 3.5.3 and finally, the perspective of job applicants in Section 3.5.4.

3.5.1 Publications Overview

The SLR identified a wide range of papers, spanning a number of countries, different topics, and unique methodologies. To understand what presently exists, and where there are gaps in the current understanding, I began by mapping publications based on their focus. Among the categorizations, I considered the hiring process itself (subdivided by phase into interview preparation, the interview process, or interview feedback/decisions), skills requested or knowledge deficiencies reported, and barriers for minoritized groups, or attempts to make the process more inclusive (split by gender and race/ethnicity). In total, 105 publications touched on these topics. The full list of publications is available at: https://bit.ly/3hVSFhq, and also presented in detail in Table 7.1 of the Appendix.

Within the publications identified, the majority (88.6% of all identified) focused on the skill gaps and knowledge deficiencies of job candidates or recent hires, and far fewer centered on the interview process itself, interview preparation, or interview feedback and decisions. While many studies may have touched on how tools could be used in recruitment, or scraping job postings to see what companies wanted, there is a need to clearly define the hiring process. Beyond the books on hiring, few researchers explicitly described the stages involved [Behroozi et al., 2020a, Raaen and Lauvås Jr, 2018, Capiluppi et al., 2013]. Although these works were incredibly beneficial in identifying components of the hiring process, the phases mentioned were more of a broad overview, and the works had other limitations. For example, in one article, the data were pulled from Glassdoor, a hiring website that allows job seekers and employees to anonymously review companies and to describe their hiring experiences [Behroozi et al., 2020a]. However, this may have captured a biased set of impressions from posters that either had extremely positive or negative experiences. Also, while they did mention that a "leaky pipeline," in which "otherwise qualified candidates are lost at some stage of the hiring pipeline" (p.71), may be an issue for underrepresented groups, they did not actually examine specific populations in this research.

In fact, many publications which mentioned diversity issues or inclusivity initiatives did provide suggestions on ways to improve the hiring process, but they did not actually perform a study on minoritized populations. Although a couple of studies examined gender in an abstract way, or may have touched on racial issues, few methodically studied race/ethnicity to assess the discrepancies in the field. A publication by Hall and Gosha (2018) was a notable example that did, offering insight on student preparation and interview anxiety among African American students at a Historically Black Institution. Going forward, I recommend that more scholars interested in technical interviews and the hiring process in computing consider the unique experiences of underrepresented groups, to provide greater insight ways of making hiring more equitable. I also suggest a particular focus towards the intersectionality of gender and race/ethnicity, which can impact perceptions and experiences [Ross et al., 2020].

3.5.2 Digital and Non-Digital Sources Important in Computing

There are many sources, both digital and non-digital that are important to the hiring process in computing, in terms of both student preparation and in terms of tools recruiters/hiring managers use for screening applicants. In Table 3.3, I illustrate a list of different digital sources, information about the primary target, and a count of their mention in the articles identified from the SLR. Websites fell into nine different categories, and while many popular ones were for professionals (LinkedIn), or a general audience (e.g., Facebook and Twitter), others were unique to computing (e.g., Stack Overflow and Kaggle). Even though some sites are not used to directly showcase an applicant's skills, companies may consider public posts on forums ways to gain insights into the candidate's thought process, and attitude [Giguère et al., 2013].

Recruiters considering these digital sources learn about the personality and skills of potential candidates [Raaen and Lauvås Jr, 2018, Papoutsoglou et al., 2019]. Publicly available information can help to identify candidates with specific capabilities, but may also reveal behavioral patterns that give companies a wealth of information without having to invest more time and money speaking with or interviewing a candidate. Among the sites used, *LinkedIn* was the most popular, followed by GitHub.

General Category	List of Sources	Links	Audience	Mentions in Publications
Software Development Sites	GitHub	http://github.com	C	19
	BitBucket	http://bitbucket.org	C	3
	Google Code	https://code.google.com/	C	2
	SourceForge	https://sourceforge.net/	C	1
	Snipplr	https://snipplr.com/	C	1
Computing and Interview Practice, Instruction, and Competitions	LeetCode	https://leetcode.com/	C	4
	InterviewBit	https://www.interviewbit.com/	C	1
	InterviewCake	https://www.interviewcake.com/	C	1
	Kaggle	https://www.kaggle.com/	C	1
	HackerRank	https://www.hackerrank.com/	C	1
	Coursera	https://www.coursera.org/	G	3
	Udacity	https://www.udacity.com/	G	2
Job Portals & Search Engines	Careers by StackOverflow	https://stackoverflow.com/jobs/	C	3
	Dice	https://www.dice.com/	C	3
	CareerBuilder	https://www.careerbuilder.com/	P	5
	Glassdoor	https://www.glassdoor.com/	P	6
	SimplyHired	https://www.simplyhired.com/	P	4
	We Work Remotely	https://weworkremotely.com/	P	1
	Indeed	https://www.indeed.com/	P	5
	Monster	https://www.monster.com/	P	8
	AngelList	https://angel.co/	C	1
Q&A	StackOverflow	http://stackoverflow.com	C	16
Professional Social Networks	LinkedIn	https://www.linkedin.com/	P	26
Profile Aggregating	Masterbranch	http://masterbranch.com/	C	5
	Coderwall	https://coderwall.com/	C	4
Social Media Networks	Facebook	https://www.facebook.com/	G	18
	Twitter	https://twitter.com/	G	16
	YouTube	https://www.youtube.com/	G	6
Social News Websites	Hacker News	https://news.ycombinator.com/	C	5
	Slashdot	https://slashdot.org/	C	1
	Reddit	https://www.reddit.com/	G	2
Studying Computing Companies: Research	BuiltWith	https://builtwith.com/	C	1
	StackShare	https://stackshare.io/	C	1

Note. C= Computing; P= Professional; G= General; A= Academia

Table 3.3: Digital sources for computing recruitment, communication, practice, and research

GitHub is a site for developing software collaboratively [Konchady, 2016, McDowell, 2014].

Additionally, several profile aggregators such as *Masterbranch* or *CoderWall* were mentioned as tools for recruitment and assessing the candidates. Profile aggregators refer to websites that collect information about the profile of an individual using data collected from different sites, like GitHub [Capiluppi et al., 2013, Konchady, 2016]. They are considered useful tools since they can provide data about the development qualifications of an individual. Another source unique to hiring in computing is Stack Overflow.

Stack Overflow is a question and answer site pertaining to computing topics, but developers also treat it as a type of coding documentation [Konchady, 2016, Xu et al., 2020]. Individual users are able to post answers to questions, which are meant to be direct rather than a lengthier discourse. The answers are subject to a form of peer review, in which other users can up or down vote how well the response addresses the question, and then user profiles contain a "reputation score" based on these votes. This score thus becomes a measure of trust based on how well the community feels the responses resolve the given issue. Note, this is separate from *Stack Overflow Careers* [Xu et al., 2020], which contains not only job postings, but also includes the curricula vitae (CVs) of the contributors.

Stack Overflow Careers is not the only computing specific job search portal. *Dice* is another for computing-field focused engine, and *AngelList* is a technology and start-up job portal that also allows investments in new ventures [Tyler, 2015]. Job seekers can use any of the general professional sites, and specifically *Glassdoor*, *Indeed*, or *CareerBuilder* are used the most frequently in research to assess computing companies' requirements [Florea and Stray, 2018, Hiranrat and Harncharnchai, 2018, Papoutsoglou et al., 2019].

In addition to the digital sources already described, there were also several other recommendations that aid in applicant preparation, and ways that recruiters might locate talent. A complete breakdown of the mention of these non-digital sources is described in Table 3.4. It should be noted that although certifications are mentioned as a consideration during hiring, especially for positions in information technology, in other areas of computing they are a controversial topic [Giguère et al., 2013, Jumabayeva, 2014, Raaen and Lauvås Jr, 2018, McDowell, 2015]. While sometimes they are seen as beneficial, other times they are treated neutrally, or even as a negative for candidates. Just like certain companies may consider a candidate being "versed in too many languages" a negative, certifications may make a candidate overly specialized. Conversely, internships were widely regarded as highly beneficial to gaining experience, and have been shown to help bridge the skill gap between what is taught in academia and experiences in industry [Tyler, 2015, Oguz and Oguz, 2019, Lara et al., 2019].

General Category	Title	Reference	Audience	Mentions in Publications
Mock Interviews	—	—	G	7
Internships	—	—	G	17
Hackathons	—	—	C	5
Certifications	—	—	C	11
Bootcamps	—	—	C	3
Computing Practice or Instruction Books	Cracking the Coding Interview	[McDowell, 2015]	C	4
	Programming Interviews: The Insiders' Guide	[Aziz et al., 2012b]	C, H	1

Note. C= Computing; H= Hiring Manager; G= General

Table 3.4: Non-digital sources for computing practice, skill development, and interview training

3.5.3 Hiring Process in Computing: Employer/Industry Perspective

In this subsection, I consider the employer/industry perspective. It should be noted that the hiring process for computing roles fluctuates depending on a company's size or preferences. Variability in the quantity and details of behavioral and technical components is common, although I will describe the process broadly (based on the publications).

3.5.3.1 Process Overview

Finding the right candidate for a job is a task reminiscent of a computing optimization problem. Often automated, it requires finding the best categorization and recruitment strategy [Raaen and Lauvås Jr, 2018]. The hiring process from the industry perspective may involve any number of steps, and may be unique to each company [Raaen and Lauvås Jr, 2018, Capiluppi et al., 2013, McDowell, 2014, Rawlings-Goss, 2019b]. In general though, most utilize a similar process across time, as depicted in the hiring procedure for computing roles in Figure 3.3. The procedure describes how job applicants enter the hiring process from one end and, stage by stage, more qualified candidates progress through until a decision is made and someone is hired.

In terms of the specific stages, hiring managers or companies typically first undergo a discovery phase, in which they obtain leads on potential applicants from options such as career fairs, coding competitions, job advertisements, recruiters, personal referrals, social networks, etc. (A). Once an applicant has been identified they will make initial contact and attempt to contact the applicant using methods such as cold calling, e-mailing, mailing directly, messaging via social media or

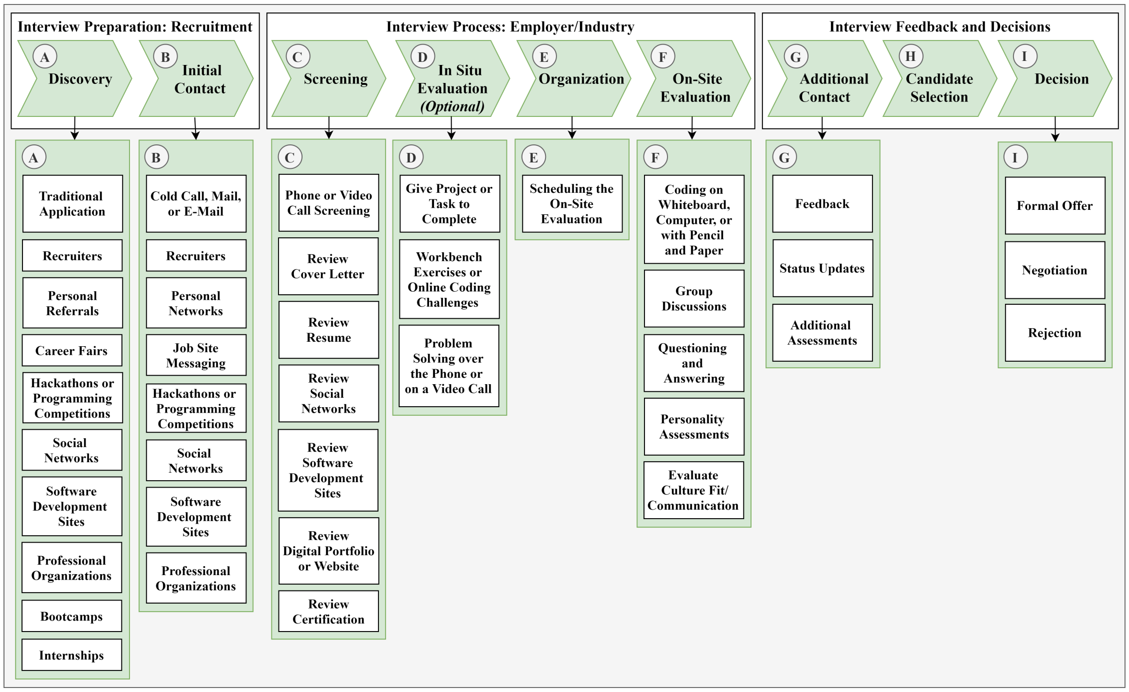


Figure 3.3: Employer/Industry hiring procedure for computing jobs

through software development sites (B). Next, they begin to screen potential applicants using items such as a cover letter, resume, phone screenings, social media, digital portfolio or website, or software development sites like GitHub or BitBucket (C). Based on what they uncover, the next step may include an in situ evaluation, where candidates are given a project or task to complete and/or online coding challenge or workbench exercises (D). However, this step is optional, and not necessarily a part of the process for all companies. Subject to the candidate's performance, they may then schedule an in-person/on-site interview. This requires organization and coordination of plans both for the candidate, and also the staff and hiring managers (E). During the on-site evaluation the candidate will likely complete several interviews to assess their hard and soft skills (F). Depending on how this phase goes (which may include multiple steps depending on the company), the final stage may involve additional contact. Further communication may include requests for additional materials or assessments (G). Then, the company will need to make a determination about whom they want to select for the role (H), before either extending an offer or rejecting the candidate (I).

3.5.3.2 Recruitment

Recruiting for a computing position can occur via multiple channels, however, hiring managers often look online for potential candidates [Capiluppi et al., 2013, Amadoru and Gamage, 2016]. *E-recruitment* is defined as a process by which individuals are matched with positions via online and off-line strategies and technology [Malherbe et al., 2015]. Increasingly, social media sites like Facebook or LinkedIn may be used for e-recruitment to identify leads, communicate, engage, interact, and attract potential computing talent with specialized skills [Singer et al., 2013, Amadoru and Gamage, 2016]. Other options for recruitment include corporate website advertisements, employee referrals, referrals through an alumni network, job fairs, local professional groups such as the Software Process Improvement Network (SPIN), IEEE, ACM, etc., conferences, customer networks, and personal networks [Rothman, 2013, McDowell, 2014].

Apart from more traditional job sites like LinkedIn and Indeed, project hosting sites such as GitHub, StackOverflow, or BitBucket are also used during recruitment and hiring to learn more about candidates through their online contributions and activity traces [Capiluppi et al., 2013, Marlow and Dabbish, 2013, Singer et al., 2013, Sarma et al., 2016, Raaen and Lauvås Jr, 2018, Papoutsoglou et al., 2019]. Often these are treated as virtual portfolios, and can provide insight into hard and soft skills [Sarma et al., 2016, Raaen and Lauvås Jr, 2018]. Technical skills may be considered not only in terms of the ability to code, but also in terms of the quality of the work, design decisions, and testing performed [Sarma et al., 2016]. However, soft skills gleaned may include information such as an ability to work well with others, determined by collaborations and comment interactions. In addition, this may also include learning about candidate's ability to manage projects, as well as a demonstration of their interest in the field, curiosity, motivation, and innovation.

Some hiring managers believe that that the activity traces may be harder to manipulate than a traditional resume, making them more transparent and less prone to bias than other sources when evaluating an applicant [Marlow and Dabbish, 2013, Konchady, 2016]. Technical recruiters even have noted that they find a lack of public activity on such sites to be an issue [Singer et al., 2013]. For example, it may be perceived as odd to not update on GitHub since it is the "factual standard at the moment for version control" [Singer et al., 2013, p. 112].

Raaen and Lauvås previously conducted semi-structured interviews with 10 hiring managers from corporations of different sizes to examine how companies may locate potential job candidates [Raaen and Lauvås Jr, 2018]. Although the study was limited to companies in Norway, they discovered that typically recruiters and hiring manager used project sites like GitHub or StackOverflow later in the selection process, after initially reaching out through LinkedIn to submit a resume [Raaen and Lauvås Jr, 2018]. Instead, the content on these sites was used as fodder for discussion of personal projects.

3.5.3.3 In Situ Evaluation

In situ evaluations are not conducted by all companies but are fairly common in computing [McDowell, 2015], particularly with the COVID-19 pandemic shifting hiring online [Maurer, 2021]. They are methods employed to assess a candidate's qualifications or skills detailed on their resume remotely [Capiluppi et al., 2013, McDowell, 2015]. Candidates often complete coding tasks or answer questions using shared documents or online platforms like HackerRank, CoderPad, Skype Interview, or interviewing.io [Behroozi et al., 2019, McDowell, 2015]. They may also entail take home assignments. Such "homework" projects completed need to not only solve the problem asked, but are also evaluated for clarity of documentation and consideration of test-driven development [Nagy, 2019].

3.5.3.4 On-Site Evaluation

Typically, on-site interviews range from half a day to several days [Behroozi et al., 2019]. They include anywhere from 3 to 6 interviews in person, each lasting 30 minutes to an hour [Giguère et al., 2013, McDowell, 2015]. Interviewers for the on-site are often given the candidate's resume a few days in advance, so questions are based off of what is presented [Jackson, 2013]. Topics covered may vary by the company and role, but the job candidate's performance is usually based on any combination of the following areas [McDowell, 2015]:

- *Analytical Skills:* Typically assessed based on problem solving questions and puzzles to determine the candidate's thought process and the time to arrive at a solution
- *Coding Skills:* Usually based on practical application in which candidate demonstrates ability to write well-organized and logical code to solve a given problem
- *Technical Knowledge and Computer Science Fundamentals:* Based on the candidate's understanding of core principles in CS and their knowledge of relevant technology
- *Experience:* May include events that show motivation and determination as well as prior projects and programs

- *Culture Fit/Communication Skills:* Pertains to the candidate's ability to express themself, and how likely they may be to get along with others at the company

Although problem-solving questions may come in many forms, the most frequent categories include [McDowell, 2014]: Estimation questions (also known as Fermi problems, e.g., estimating pizzas eaten in the U.S. annually); case/business questions (e.g. how to launch a product in a specific market); design questions (about an actual or made up product); and brainteasers.

3.5.3.5 Feedback and Decisions

Often feedback on the candidates' performance is given directly to a hiring manager and/or committee, or discussed at a group meeting, although recommendations can also be submitted for review later [McDowell, 2015]. Rothman also suggests that if an employee leaves voluntarily, they should be involved in selecting their replacements since they will have the best knowledge of the job [Rothman, 2013]. Typically, it takes about a week after the on-site interviews for employers to provide feedback about the next steps — whether this entails additional information, further interviews, a formal offer, or a rejection [McDowell, 2015].

3.5.4 Hiring Process in Computing: Job Seeker Perspective

In this subsection, I consider the job seeker's perspective of the hiring process in computing. I will not discuss in situ evaluations or on-site interviews in detail for jobs seekers since they are similar to what was described already, except from the alternative perspective.

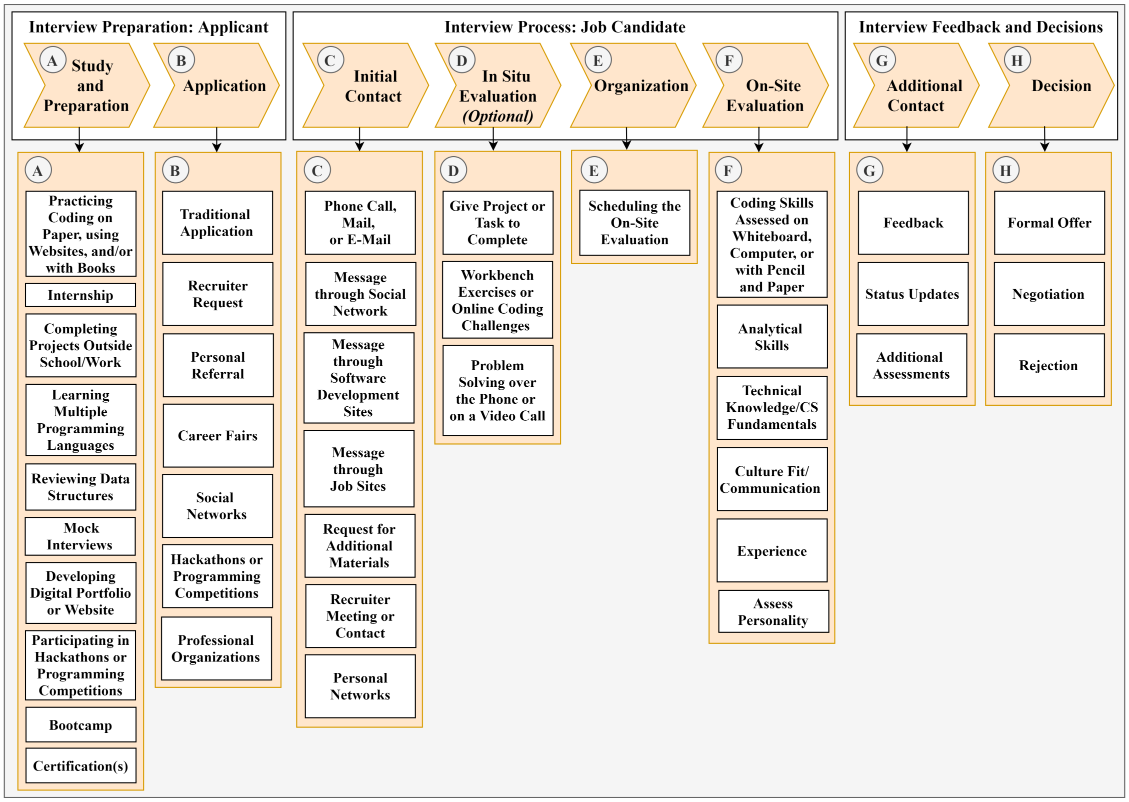


Figure 3.4: Hiring procedure for job seekers

3.5.4.1 Process Overview

Computing interviews often involve multiple steps, and different stages in the process may require varying levels of interaction and time commitments from the job seekers [Behroozi et al., 2019, McDowell, 2015, Behroozi et al., 2020a, Rawlings-Goss, 2019b, Nagy, 2019], as illustrated in Figure 3.4.

First, there are a number of study and preparation methods recommended for computing applicants, such as practicing coding on paper or with books or websites, completing an internship, practicing with mock interviews, learning multiple programming languages, etc. (A). Then, the applicant is either contacted by a recruiter, or they apply themselves (B). Depending on the applicant's suitability for the position, a hiring manager or human resource personnel will then contact the applicant, to request additional materials or do an initial screening (C). Next, an in situ evaluation may be performed, either over the phone, with a video call, using an online assessment tool, via a shared coding platform, or with a homework assignment (D). If their performance is deemed successful, the next step may involve an on-site visit and the hiring company will organize the interview for the candidate (E), including scheduling and travel arrangements. Then comes the on-site evaluations themselves (F), described further below, which tests the candidate on hard and soft skills including analytical skills, coding skills, technical knowledge and CS fundamentals, experience, and culture or fit and communication. At some point after the interview, typically around one week, the candidate hears back from the employer about their status, and additional evaluations are scheduled if needed (G). Then, if the candidate was successful, they receive a formal offer and negotiations may ensue (H).

3.5.4.2 Interview Preparation

The greatest difference between the employer perspective, and that of the job seeker is the study and preparation required for the technical interviews. Typically such preparation involves mock interviews, tutorials, preparatory books, practice websites, and code katas [McDowell, 2015, Gant, 2019a]. *Code Katas* are described as exercises for programmers that enable them to hone their skills and develop their coding ability [Gant, 2019a]. It is suggested that in addition to gaining practice, the repetition is critical for programming mastery. More generally, it should be noted that repetition aids in long-term memory consolidation and learning — a concept for which there is a lot to unpack further, but is beyond the scope of the current work [Tulving, 1966, Hauptmann and Karni, 2002].

Presently, no common source exists for applicants to obtain all the necessary information that they will need for all positions because each role and company has their own needs. However, applicants are encouraged to study. It is recommended that preparation should begin months or even years prior to applying, and if possible, programmers should attempt to code daily to maintain their skills [Aziz et al., 2012b, McDowell, 2015, Gant, 2019a, Nagy, 2019]. Preparation for hiring can also include methods such as gaining experience in an internship, working on projects outside of coursework, learning multiple programming languages, enrolling in a bootcamp, or participating in a coding challenge or hackathon [McDowell, 2015, Nagy, 2019, Aziz et al., 2012b, Raaen and Lauvås Jr, 2018, Kapoor and Gardner-McCune, 2020, Nagy, 2019]. It is further suggested that applicants develop their portfolios online, collaborating on side projects on GitHub, contributing to Stack Overflow, and creating a personal website to showcase work [Raaen and Lauvås Jr, 2018, Nagy, 2019, Konchady, 2016].

3.5.4.3 Feedback and Decisions

The way that candidates are treated, and how much information they receive can have a huge impact on their perception of the process and the company [Rawlings-Goss, 2019b]. Communication about the application status and whether or not they qualify for the next step can be critical to a candidate [Behroozi et al., 2020a]. Hiring managers should be cognizant that extra hurdles, extensive deadlines, and poor communication can repel candidates who are high in demand [Rawlings-Goss, 2019b].

In addition, the interviewer's approach and demeanor can make a big difference in how the candidate feels post-interview [Behroozi et al., 2020a]. Qualitative analysis of reports from Glassdoor have demonstrated both positive and negative approaches and their impact on the overall experience. Often computing candidates report that the interviewer can be overly harsh, critical, and condescending. This type of behavior only further exacerbates the stress during an already tense situation. Meanwhile, candidates report that if the interviewer is friendly and respectful, it can help cushion the blow even if they are rejected later.

3.6 Discussion

In this section, I discuss the major findings of the publications and their implications. In Section 3.6.1, I begin by describing issues identified with the hiring process, and concerns related to bias or a lack of inclusivity. Then, I present the value of creating a diverse workplace, and suggestions from the literature in Section 3.6.2. Finally, I provide additional recommendations for change in Section 3.6.3 for industry and academia, and then situate suggestions that may encourage minoritized students to leverage their own capital, as described by the CCW model.

3.6.1 Issues with Hiring in Computing

Literature suggests that computing students are often unaware of what to expect from technical interviews, and unsure of how they should study or prepare for them [Hall Jr and Gosha, 2018, Kapoor and Gardner-McCune, 2020, Behroozi et al., 2020a]. Frequently, they rely on knowledge gained from classes, and often report learning which skills are needed, and how questions are asked, after unsuccessful prior attempts at securing a position, or via recommendations from peers, recruiters, and others that have previously passed the interviews [Kapoor and Gardner-McCune, 2020]. Although all students may struggle with this, scholars have suggested that Black and Hispanic students may be even less familiar with the hiring process in major computing companies than White or Asian students [Bui and Miller, 2016, Hall Jr and Gosha, 2018]. Compounding the problem, professors may have very little experience with such interviews themselves, making it difficult for them to adequately prepare others [Hall Jr and Gosha, 2018].

Beyond the classroom and students' preparation, there are also concerns about the inclusivity of recruitment practices. Wynn and Correll examined the effects of gender bias in the technology recruitment process [Wynn and Correll, 2018]. They noted that references to geek culture (presentations with mentions of Star Trek, Star Wars, Game of Thrones, Lord of the Rings, etc.) and gender stereotypes (e.g. slides with sexualized females, males acting macho in the role of soldiers or astronauts) reinforce the notion of a gender divide for the field, leading to further discouragement of women. Also, mentions of the perks that result in "never having to leave the office" further emphasize that a company places minimal emphasis on a work-life balance. This type of gender bias has also been confirmed by interviews with employees [Blincoe et al., 2019]. To remedy the situation, companies should reconsider their recruitment approach to make it more inclusive. Using females and racially and/or ethnically diverse role models in the presentations, and as the presenters, could help to broaden participation. Additionally, making descriptions of the technical work more affable and penetrable, along with highlighting the potential real-world impacts across different fields, could make the career path more attractive to all groups [Wynn and Correll, 2018].

In addition, it is important that hiring managers are aware of the gender-bias that pervades many of the online communities used for recruitment. Stack Overflow is one notable example, where women are often underrepresented [Vasilescu et al., 2012, Ford et al., 2017b]. As demonstrated by Vasilescu et al. (2012), women are less likely to become involved for many reasons, among which are fear of unfriendly or hostile reactions to their posts, a lack of self-efficacy, and finding the community to be intimidating. However, having even one female active in a thread makes a female more likely to participate [Ford et al., 2017b]. Also, although GitHub does not explicitly request information about gender, research by Terrell et al. [Terrell et al., 2017], using profiles backed by social media accounts, demonstrates this site has an implicit bias as well. Although women on the site may be more competent, they tend to receive less acceptance for their contributions when gender is more explicitly identifiable.

Later stages in hiring may also be problematic. Looking at callback rates for fictional candidates broadly in the U.S. labor market, Whites receive 36% more callbacks than African American applicants, and 24% more than Latinx candidates [Yarger et al., 2019]. Moreover, prior work by Wang and Redmiles (2019) in which software developers from organizations in the United States were tasked with choosing a "software architect" candidate for an onsite interview, demonstrated a strong predilection for favoring males in this leadership role. The same bias existed even for a general position. Although both candidates were presented with comparable education and experience, the hypothetical female candidate experienced an implicit bias, demonstrating the problem with hiring practices in computing. Furthermore, there was a huge divide in perceived gender roles, for which a strong effect was observed for women's connection with home and family, whereas men were associated with career and work. Such mentalities and biases can create a massive barrier for broadening participation in the field.

Rather than embracing individualism and the unique contributions that different populations can bring, companies instead want to know that a candidate will be a team player that will "fit into the culture" of the computing workplace. However, this is language that is often used to deny any diverse candidates an opportunity

[Liu, 2006, Wilson and Parker, 2007]. Although they want candidates to be knowledgeable and assertive, they do not want them to be arrogant or cocky [Nagy, 2019]. They want candidates that have hobbies outside of computing to demonstrate they have a work life balance, while also having developed a well fleshed out portfolio of side projects [Nagy, 2019, McDowell, 2015]. Taken together, this confusing, and sometimes paradoxical portrait of the ideal candidate as friendly and outgoing, ambitious, technically adept, having an impressive portfolio, managing to make time for charity, hobbies, friends, and family, while showing passion for computing and their work, is overly convoluted. Moreover, it certainly limits candidates who may not fit into this mold, or those who may be limited in the time they have to prepare for the hiring process based on their other commitments.

3.6.2 Valuing Diversity

There are numerous benefits to increasing diversity in computing hiring — financial, moral, and the advantages of increasing the unique perspectives brought to the workplace [Camp, 2012, Trauth et al., 2012, Yarger et al., 2019]. Mixed-gender teams tend to see a 26-42% greater submission of IT patents than teams comprised only of males or females [Camp, 2012]. Moreover, when looking at the financial performance of major Fortune 500 companies, an increase in female executives delivers a higher return to shareholders and a higher return on equity relative to companies with lower representations of women, at 34% and 35.1%, respectively. A congruence of racial diversity in upper and lower management of high tech firms has also been shown to promote productivity and to foster "knowledge-based" views [Richard et al., 2020]. Yet, despite the clear value to increasing diversity, hiring still lags behind and the literature surrounding attempts to increase inclusivity and expand diversity is fairly limited.

Two major papers that consider how diversity, equity and inclusion (DEI) may play a role in hiring were conducted using online sources which do not offer insight into the perspectives of minority populations [Behroozi et al., 2019, Behroozi et al., 2020a]. Instead, recommendations were made based on general notes on the interview process, and included commentary that it should be made more inclusive. The first was the study previously mentioned, using data from Glassdoor to examine reactions during different stages in the interview process [Behroozi et al., 2020a]. The other paper utilized accounts of interviews gathered from Hacker News, which noted that the current process might filter out candidates with diverse backgrounds [Behroozi et al., 2019]. However, 95% of the posters on Hacker News are male, which may lead to a skewed perception of the process. Since neither of these feedback sources allowed for description of the demographics, nor examined individual hiring encounters over time, only a correlation could be established, and they were unable to capture the experiences of underrepresented groups. Although the sources examined may have lacked an unbiased perspective, the authors made several useful recommendations on the ways the hiring process could be made more inclusive.

Behroozi et al. [Behroozi et al., 2019, Behroozi et al., 2020a] suggested using basic questions for initial screenings, since candidates may not have time to prepare adequately for phone interviews. Additionally, they proposed that the hiring process and scoring criteria should be made clear to all, as ambiguity could give an unfair advantage to those who may not have interviewed before. They also advocated for companies and hiring managers to offer alternative forms of interviews, to assess problem solving, while reducing the anxiety depending on the individual comfort level. For example, some candidates may prefer extra time to think a problem over privately, rather than having to immediately solve in a more "public" fashion. Also, candidates may prefer explaining problems with a pencil on the paper or on a computer using an integrated development environment.

Additionally, prior literature has examined perception of skills, in terms of their masculization and feminization, and how hiring diverse populations can contribute to ensuring a more balanced workplace [Trauth et al., 2012, Rothman, 2013]. Trauth et al. examined gender stereotypes about skills and knowledge in the field at three predominantly White institutions (PWI), four classified as Hispanic serving institutions and five classified as historically Black colleges and universities, and found very different opinions based on the intersectionality of participants [Trauth et al., 2012]. Although innovation was considered important for ensuring success in technology, survey respondents tended to view creativity as being a feminine characteristic (for all respondents except Black males).

It was noted that increasing diversity can be beneficial to the soft skills of a workplace, and consideration of the intersectionality of individuals can play a critical role in leveraging the assets of women that self-identify as a racial/ethnic minority. For example, in immigrant families often the English-speaking children take on the role of translators and engage in "brokering" with their parents or caregivers, a practice by which they interpret culture, language, and media to their parents to help them understand and to include them in the local community. This phenomenon is particularly common in Hispanic families, and Latina adolescents are the most likely to act as brokers. Engaging in this role improves their communication, problem solving, and negotiation — all soft skills which are critical to success in computing fields [Ahmed et al., 2013, Trauth et al., 2012, Stevens and Norman, 2016]. Thus, when recruiting, and during hiring, it is important to consider the cultural wealth that different groups can contribute to the workplace.

3.6.3 Recommendations for Change

3.6.3.1 Industry

Despite many reports that "hiring is broken," few publications address how to remedy the process, and even less discuss how the process may discourage women, Blacks/African Americans, and Hispanics/Latinxs. Scholars note that even when these groups are represented at a company, they are often working in roles other than software engineers [Lara et al., 2019]. To broaden participation in computing, it is necessary to recruit a diverse set of candidates and to consider inclusive practices supportive of marginalized groups. Companies have taken steps towards doing so, however, there is still more to be done to achieve representation more reflective of the general population. It is worth approaching the hiring process with a critical eye and asking, "How do current hiring practices overvalue certain, narrowly-defined ways of knowing as 'hard skills' vs 'soft skills'?" Furthermore, consideration should be given to how this binary benefits and harms certain cultural identities, and limits the diversity of ways to demonstrate value to a company. Earl Pace, one of the founders of Black Data Processing Associates, pointed out that persons in charge of hiring have a unique position to affect change in terms of broadening participation, and to give opportunities to minority professionals that are well qualified for the roles [Aspray, 2016].

Whether or not formal policies exist to make the hiring process more egalitarian, there are actions that can be taken [Whitney et al., 2013]. To begin, companies can undertake an internal audit of their current state in regards to DEI [Kraus, 2020]. Not only will this provide a numerical breakdown of employee representation and retention, but it can also serve to determine whether minoritized populations are assessed the same way as majority populations during hiring and in performance reviews. While companies should focus on finding skilled workers, it is important to consider implicit biases in job descriptions and recruitment practices, and the ways they may discourage candidates during the process [Lunn et al., 2021b].

Along these lines, it has been suggested that recruitment efforts should consider additional sources of talent beyond the “top-tier” universities, which may limit the scope and reduce diversity and hiring potential [Rawlings-Goss, 2019b]. Instead, scholars recommend recruiting from “mid-tier” schools, community colleges, or other venues that promote inclusion like HBCUs, HSIs, professional organizations (e.g., Women in Technology or the Association for Women in Computing), or non-profit coding bootcamps [Whitney et al., 2013, Grossman, 2012, Behroozi et al., 2020a, Rawlings-Goss, 2019b]. This could result in finding high achieving students, which can be combined with training to produce a high payoff [Rawlings-Goss, 2019b]. Although not all companies employ this approach, it is becoming more common. Roughly one in five scholars that attend Grace Hopper conference report that they receive job offers as a result of the conference [Whitney et al., 2013], which is an encouraging start. This finding presents a positive case for recruiting more diverse talent from other similar gatherings or venues like Tapia, the Latinx Tech Summit, and/or the National Society of Black Engineers Convention [Whitney et al., 2013, Grossman, 2012, Behroozi et al., 2020a, Rawlings-Goss, 2019b].

While this SLR emphasized variability in what companies may want, and which skills they value, several important considerations should be taken away. For example, despite differences in the processes and demands across industries and roles, communication and teamwork are widely considered necessary [Matturro, 2013, Stevens and Norman, 2016, Ford et al., 2017a, Watson et al., 2017, Scaffidi, 2018a, Craig et al., 2018, Garousi et al., 2019c, Oguz and Oguz, 2019, Dubey and Tiwari, 2020]. Given their value, it is imperative for educators and employers to think about how they can foster development of these skills for students and employees.

3.6.3.2 Academia

Although academic institutions may not be involved in hiring itself, they can help prepare students for their careers, and work towards broadening participation in the field. Firstly, recruitment and retention of students may play an important role in production of diverse sets of qualified graduates, who may eventually become job candidates. As such, it is vital to examine the factors that may influence decisions to enroll in computing and those which may contribute to students' engagement. Likewise, it is critical to evaluate the underlying causes for major switching behavior (e.g., to business, history, or other engineering fields). Previously, scholars have argued it is important to develop students' disciplinary identities in STEM fields, in addition to their cognitive skills [Calabrese Barton and Tan, 2019, Vakil, 2020, Calabrese Barton et al., 2020]. Departments should also consider that diverse faculty may serve as mentors and role models [Bettinger and Long, 2005, Charleston et al., 2014], and that improving parity in representation "may help mitigate the educational climate, which our participants described as isolating and insensitive to their needs" [Charleston et al., 2014, p. 174]. In addition, instructors should be judicious in the way they speak with students, and the feedback they give on exams and assignments. When delivered in the right way, constructive feedback can help improve pedagogy and can encourage and maintain hopes and dreams despite setbacks [Rittmayer and Beier, 2008].

Furthermore, to encourage students' professional and community development, departments should raise awareness of the different discipline-specific groups and organizations available for students early in their studies (e.g., Society of Women

Engineers, Society of Hispanic Professional Engineers, STARS Computing Corps). They could also form partnerships with local companies, and could create panels comprised of diverse employees to share their pathways to computing, and to answer questions. Not only could these speakers serve as inspiration and/or role models, but it could provide students with the opportunity to ask questions they may have without the pressure of a formal networking session or interview interaction. Additionally, to ensure more equitable development in the future, educators can also include course material to train students on algorithmic bias. It is important that students can recognize and detect "intentional discrimination, statistical and classification bias, as well as data errors and absences that may perpetuate structural disadvantage" to shift the mindset towards one of inclusivity [Yarger et al., 2019, p. 389]. Such training is vital towards students' development of knowledge and skills that will yield consideration of fair-minded practices and implementation.

3.6.3.3 The Role of CCW in Change

To enable students and job applicants to achieve long term success in computing, it is important to provide support and promote leveraging their own capital. As described by the CCW model, there may be multiple avenues to do so for minoritized populations. In the discussion that follows, I will tie the hiring process to specific opportunities to honor cultural wealth.

Social Capital: In professional settings pair programming has been shown to have several benefits [Begel and Nagappan, 2008]. Not only does it result in higher quality code with fewer bugs, but partners often learn from each other, leading to better understanding. Diversity in thought has also been shown to enhance the work developed by the team, as partners contribute unique perspectives to a given task. Likewise, universities can apply this approach to programming coursework, including pair-programming projects or assignments, and potentially rotating teammates to increase exposure to disparate approaches and thinking. Building these relationships with others in their classes, whom they may otherwise be uncomfortable approaching, could help students develop their ties within the computing community. This interaction could improve social capital and build support they can lean on during the hiring process. In addition, assigning students to diverse groups for projects, rather than allowing students to choose their own teammates, is recommended to more accurately reflect scenarios encountered in the workplace [Nagarajan, 2011].

Even before hiring begins, employers should seek to offer career training or internship opportunities to underrepresented groups to encourage occupational trajectories in computing [Charleston, 2012, DuBow, 2014]. Alternatively, co-operative education programs (or "co-ops") are similar to internships, but typically last longer, and involve a partnership with an educational institution to offer academic credit for work completed with a company [Tyler, 2015]. Although it may require a greater investment of time and resources, co-ops lead to job candidates with improved preparation and technical acumen.

Furthermore, purposeful leadership, and placing women and/or minorities as members on industry boards can also lead to more diverse mindsets, leveraging human capital, and could encourage representation of others within the company as well [Sandgren, 2014]. It is also important to think about the staff representing the company. Mahmoudi mentioned that typically the human resources managers that greeted candidates for the on site visit were female. However, later interviews during the course of the on site were often all White or Asian males, and usually more senior employees [Mahmoudi, 2017]. Accordingly, presenting candidates with more diverse individuals they may self-identify with during hiring, especially in a range of roles, could affect their perceptions of the company, and could work towards creating a more inclusive environment [Whitney et al., 2013]. It may demonstrate that a candidate will be able to find a community within a company, and foster development of social capital.

In addition, mentors have been shown to provide guidance and support to underrepresented groups [McDowell, 2014]. As such, companies could also develop initiatives to include mentoring within the workplace as part of their on-boarding for new hires. By creating more transparent tracks, with built in mechanisms for training and support, organizations can work towards broadening participation.

Familial Capital: Prior literature has described how resumes can be used to perpetuate inequity in hiring across industries and occupations, and have highlighted how employers' inherent bias may result in neglecting qualified applicants based on presumptions about their identification with a particular gender, racial, or ethnic group [Yarger et al., 2019]. To mitigate discrimination during application screening, programs have been developed (such as Blendoor[1]) to remove personal information from resumes with the intention of encouraging employers to focus on applicant's skills. However, since adaption of such technology may not be widespread, companies should consider other avenues for locating qualified candidates, and particularly those who may otherwise be overlooked based on human judgements about their name or the academic institution they attended. It has been noted that often the best candidates are obtained through peer referrals, where a friend, mentor, or colleague can vouch for the skills of a job applicant [McDowell, 2014]. By tapping into the networks of trusted employees, companies may be able to locate adept applicants that have the capability to succeed in the role, but that may have been neglected while parsing through resumes as a result of human or algorithmic bias.

[1] https://blendoor.com/

Also, leveraging familial capital through hiring an employee's immediate, extended, or chosen family may lead to better workplace relationships, increased collaborations, and higher productivity. However, it can be a slippery slope to perpetuating nepotism and additional inequity, and while such channels may be beneficial for identifying applicants, all job candidates should be subject to the same interview process to assess hard and soft skills.

Navigational Capital: Institutional agents such as faculty have been shown to play an important role in recognizing students' inherent capital, and encouraging them to succeed [Denton et al., 2020]. To ensure optimal performance during interviews, hiring managers and recruiters should consider their own impact and should make an effort to provide positive support and encouragement. This is important since previously critical, harsh, or condescending interviewers have been shown to leave a lasting impact on candidates [Behroozi et al., 2020a]. Interviewers must be cognizant of their influence, and rather than appearing stoic or overly trenchant, could offer support in the form of tips, and positive reinforcement to help bolster students' navigational capital as they solve difficult problems during technical interviews.

In the interview itself, it may be important to consider practices that ensure a candidate has the capability of performing the job, without requiring intensive practice to prepare. Whether a candidate is fresh out of school or more advanced, they should be treated the same and the approach should be equal. Rather than offering a rigorous programming test to assess their abilities, a better approach would be to ask questions or problems that employees at the company recently solved. This method ensures that irrespective of the candidate's experience level, they can demonstrate their approach and problem solving acumen in a concrete way to the types of things they would need to do in the role [Neville-Neil, 2011]. After it has been established that the candidate does possess the foundations to perform the job, there are other ways to gauge skill that could be more equitable to assess hard and soft skills like creativity, critical thinking, and communication.

Another option both for universities and companies is to consider collaborating to offer opportunities for mock interviews, which can help to reduce job applicants' anxiety, strengthen communication skills, and can help them navigate through the hiring process [Hall Jr and Gosha, 2018, Snell-Siddle et al., 2014]. It has been suggested that since students often encounter "friendly teams" during meetings at school, mock interviews can help them gain insight into how meetings are conducted in an industry setting [Nagarajan, 2011]. They can also help students utilize learning transfer as they apply theories taught into practice.

In addition, since students report an abundance of focus on theory, educators should ruminate on providing increased opportunities for hands on examples and problem solving. Project work and simulations that tackle real life problems or role playing, have been shown to be a valuable aspect of university studies, and can be beneficial when students complete technical interviews [Nagarajan, 2011]. While universities are not meant to serve as vocational institutions, increased familiarity with how algorithms can be applied, and in which contexts, may reinforce the concepts covered. Also, embedding the mindset of testing throughout design and development could help to improve the quality of the work submitted on exams and assignments, as students become stronger at walking through their solutions and correcting their own errors [Craig et al., 2018].

Resistant Capital: As a first step, companies should provide inclusivity training to all employees. Interviewers and hiring managers should consider how their demeanor and disposition can impact (and potentially discourage) job candidates. Many students report that during the hiring process they feel the recruiters are poor at conveying information, and they are often “ghosted” [Behroozi et al., 2020a]. *Ghosting* is defined as the phenomenon when during communication, one party suddenly disappears and stops contacting the other. Providing feedback about the performance should be considered carefully, to encourage aspirational capital for job candidates. Offering concrete suggestions, like specific data structures to review, can be beneficial. Alternatively, describing the ways the student could improve, along with giving encouragement to reapply once they have mastered whatever area they fell short in, could enable the job seeker to learn from the experience and move forward in a positive way despite the present failure. Rather than crushing their hopes, proper framing could help strengthen their resistant capital, encouraging them to prepare more in support of their goals, despite the temporary setbacks.

Companies should also consider their job postings, the way they discuss the corporate “culture” during recruitment sessions, and how technical complexity or certain references (i.e., geek culture, gendered, or racial/ethnic) may discourage applicants [Wynn and Correll, 2018]. Job descriptions should be reviewed by multiple team members, perhaps anonymously, to avoid alienating any individual. In addition, the programs employed to sort through resumes and identify candidates, should be analyzed and checked to mitigate potential algorithmic bias.

To ensure more equitable development in the future, educators can also include course material to train students on algorithmic bias. It is important that students can recognize and detect “intentional discrimination, statistical and classification bias, as well as data errors and absences that may perpetuate structural disadvantage” to shift the mindset towards one of inclusivity [Yarger et al., 2019]. Such training is vital towards students’ development of knowledge and skills that will yield consideration of fair-minded practices and implementation.

Linguistic Capital: Although non-native speakers were encouraged to conform for interview preparation, we recommend that employers consider the benefits of hiring multi-lingual individuals. Speaking another language (or multiple languages) should be considered an asset that may make them more adept at sharing their work and explaining their code during the hiring process in the short term [Trauth et al., 2012, Stevens and Norman, 2016]. In the long term, it could also translate into a potential employee that can effectively communicate not only with their boss and coworkers, but also with clients when trying to elicit specifications for software or describing a product. Rather than placing such a premium on live coding during hiring, interviewers could offer candidates more opportunities to talk through prior projects, or to explain take home assignments.

Aspirational Capital: There are several other things that employers could do to encourage hiring and retention of employees. Blincoe et al. (2019) demonstrated that women often feel they have to work harder to prove their value, and that there is an implicit bias that disadvantages women towards receiving promotions; however, this is likely true of many minorities. Promoting work life balance, offering mentoring opportunities for new employees, and ensuring promotions are based on measurable achievements could help to improve diverse talent and create a more equitable environment.

Overall, the publications identified through this SLR demonstrate that there are a number of concerns related to hiring in computing, and that work is required to make the process more equitable. Industry needs to rethink the impact of current practices, and how they may discourage populations already underrepresented in the field. Furthermore, academic institutions can help to make students cognizant of what to expect, and offer resources to guide their preparation and development. In addition, as subsequent studies are conducted on hiring in computing, it is vital for researchers to consider the needs of diverse students, and to investigate the differential experiences and situations that may affect job candidates' performance in interviews.

3.7 Limitations

There are some limitations which should be mentioned. Source selection was conducted primarily by the first author of this paper, which may lead to some subjective bias. Also, although the search terms were based on a preliminary assessment and seemed to cover the subject adequately, additional terms might have identified further sources. Future researchers should consider doing so, and could also give more consideration to sub-specializations within computing fields such as human computer interaction, data science, machine learning (ML), networking, or bioinformatics. Moreover, expanding the quantity and range of repositories searched may result in additional publications that offer different perspectives.

It should also be noted that each company may have their own hiring procedures, and differences may exist depending on the role. As such, there may be others that are unique, which were not examined here simply because there were no formal publications about their process. In addition, although the publications gathered span many countries, and multiple continents, the sources were limited to papers in English. I would like to acknowledge that there may be additional work that was filtered out in the review which may be applicable, and I recommend future studies consider inclusion of papers from other databases or written in other languages.

3.8 Conclusions

Ultimately this work serves to inform students and educators about the hiring process, and how to prepare. Tweaks to the curriculum, and offering additional preparation earlier, could help new graduates to navigate through the hiring process with less stress. Furthermore, the findings from this research are intended to provide industry with evidence of the problems inherent with the existing hiring system.

Although diversity in the computing workplace is widely acknowledged to be important, women, Black/African American workers, and Hispanic/Latinx workers are woefully underrepresented relative to their proportions in the general population. Moreover, the present literature is deficient in discussing how workplace initiatives to broaden participation are applied during the hiring process itself. Despite clear evidence of fiscal and cultural benefits to increasing diversity, neither industry nor academia seems to have a handle on how to address these issues, nor are there widespread attempts to remedy the existing hiring process. However, considering the factors that contribute to imbalances is important, and if tools such as GitHub or Stack Overflow are being used for recruitment, it is necessary to consider the huge gender gap in contributions to these sites [Ford et al., 2017b, Wang et al., 2018]. Furthermore, future research should contemplate analyzing how individuals from different backgrounds perceive computing interviews qualitatively, to try understand what the phenomenon of hiring looks like for everyone, and not just those racial/ethnic groups that voice their opinions on public forums.

Going forward, it is important for the computing industry to consider how current practices may limit diversity. Expanding recruitment sources, being transparent about what they expect from applicants, and communicating effectively with job candidates about their status during the process could positively impact job seekers. Knowing that "hiring is broken" in computing is not enough. Instead, it is important to consider the why and to engineer solutions.

CHAPTER 4

TECHNICAL INTERVIEW PREPARATION AND IMPACT OF CULTURAL EXPERIENCES

To attain a computing job, applicants are encouraged to prepare months, or even years before they begin looking for a position. Yet this expectation neglects to consider the obligations and responsibilities students already have. The goal of this study was to answer RQ2 of the dissertation: How do cultural experiences impact technical interview preparation? In order to learn about the experiences of students that identified with different gender, racial, and ethnic groups, quantitative analysis was performed using a survey administered at three metropolitan universities in Florida. It should be noted that the work presented here, is from a publication presently in press, [Lunn et al., 2021b].

4.1 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.

4.2 Introduction

Between 2019 and 2029, demand for workers in computing occupations are expected to surge 28.8% [U.S. Bureau of Labor Statistics, 2019]. 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 [Rawlings-Goss, 2019a, Mandel and Carew, 2015, Echeverri-Carroll et al., 2018].

Major technology companies like Google, Facebook, and Twitter admit that their diversity is not where it should be [Mandel and Carew, 2015, Gosha et al., 2019]. Their workforce is 60% White, 30% Asian, and 6% or less are composed of Hispanic or Black workers [Mandel and Carew, 2015]. At all three companies, women were only 30% of the total employees. Given the preponderance of White and Asian males in computing [Mandel and Carew, 2015, National Science Foundation, National Center for Science and Engineering Statistics, 2019], 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 [Hall Jr and Gosha, 2018].

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 [Barr, 2017, Farnsworth and Holtzblatt, 2016, Mandel and Carew, 2015, Hall Jr and Gosha, 2018, Rodriguez and Lehman, 2017]. 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 [Gosha et al., 2019]. 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) [Behroozi et al., 2020a, Behroozi et al., 2018, Hall Jr and Gosha, 2018].

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 [Behroozi et al., 2020a, Behroozi et al., 2018, McDowell, 2015]. 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 [McDowell, 2015]. 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%) [Carnevale and Smith, 2018]. 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 [Carnevale and Smith, 2018]. 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) [Carnevale et al., 2015], who often are dealing with increased cultural responsibilities such as caring for children or other members of the family [Carnevale and Smith, 2018].

While there is a small subset of scholarly literature dedicated to examining the "leaky hiring" procedure and what is expected during the hiring process in computing [Ford et al., 2017a, Behroozi et al., 2020a], 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 chapter-specific research questions (denoted C4RQ#):

- **C4RQ1:** *How do students prepare for technical interviews?*
- **C4RQ2:** *How do differences in personal situations and cultural experiences impact preparation time for technical interviews?*
- **C4RQ3:** *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 [Lent et al., 1994, Lent et al., 1999, Lent et al., 2002, Lent et al., 2011], 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 [Adelman, 1988, McCurdy et al., 2004, Cultuur, 2014]. 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 chapter, we will first review the background work in Section 4.3. Then, we will discuss the theoretical frameworks driving this research in Section 4.4. In Section 4.5, we detail the methods including the survey conducted, demographics of the population of study, and statistical analysis. Then we provide the results in Section 4.6, and a discussion of the findings in Section 4.7. In Section 4.8 we describe the limitations of our work, and we conclude in Section 4.9 with a summary and suggestions for future work in the field.

4.3 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 [Behroozi et al., 2020a, Behroozi et al., 2018, McDowell, 2015]. 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 [Behroozi et al., 2018]. 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 [Burnett et al., 2016]. 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 [Hall Jr and Gosha, 2018].

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 [Behroozi et al., 2019]. 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 [Salvi et al., 2017, McDowell, 2015, Gant, 2019a, Hall Jr and Gosha, 2018, Aziz et al., 2012b]. 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 [McDowell, 2015, Aziz et al., 2012a].

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 [Behroozi et al., 2019], and through Glassdoor [Behroozi et al., 2020a]. 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" [Behroozi et al., 2019]. 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 [Behroozi et al., 2019, Behroozi et al., 2020a]. On HackerRank, 95% of users were male, and there was no information about the race/ethnicity of participants [Behroozi et al., 2019]. 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 [Behroozi et al., 2020a]. 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 [Hall Jr and Gosha, 2018]. 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.

4.4 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 4.4.1 and CCW in Section 4.4.2.

4.4.1 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 [Lent et al., 1994, Lent et al., 1999, Lent et al., 2002, Lent et al., 2011]. Derived from Bandura's general social cognitive theory [Bandura, 1986], self-efficacy, outcome expectations, and personal goals are central facets of the framework, and are considered foundational aspects for career development [Lent et al., 2002]. Applying a bidirectional causality

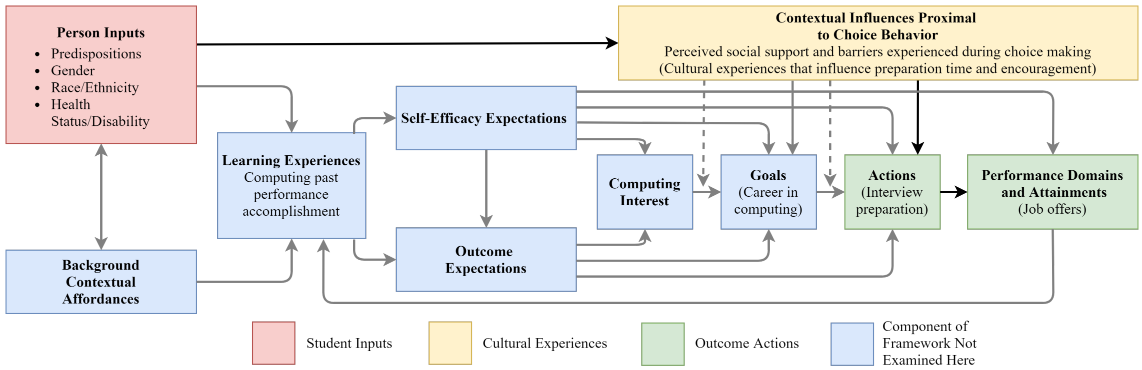


Figure 4.1: Overview of social cognitive career theory (SCCT) as it pertains to students seeking computing positions

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 4.1, adapted from a combination of Lent et al. [Lent et al., 1994] and other STEM-specific researchers [Luttenberger et al., 2019, Navarro et al., 2007]. 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 [Wu, 2009]. 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 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" [Fouad and Santana, 2017]. Previously, the SCCT model has accounted for interests and persistence goals of students in computing [Lent et al., 2008]. 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) [Lent et al., 2011]. 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.

4.4.2 Community Cultural Wealth Model

To better explain our findings, we also employed the **Community Cultural Wealth (CCW) model**, as shown in Figure 4.2. Developed by Yosso [Yosso, 2005], the CCW model builds on critical race theory epistemologies and applies an anti-deficit approach [Harper, 2010] 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" [Yosso, 2005, p. 77].

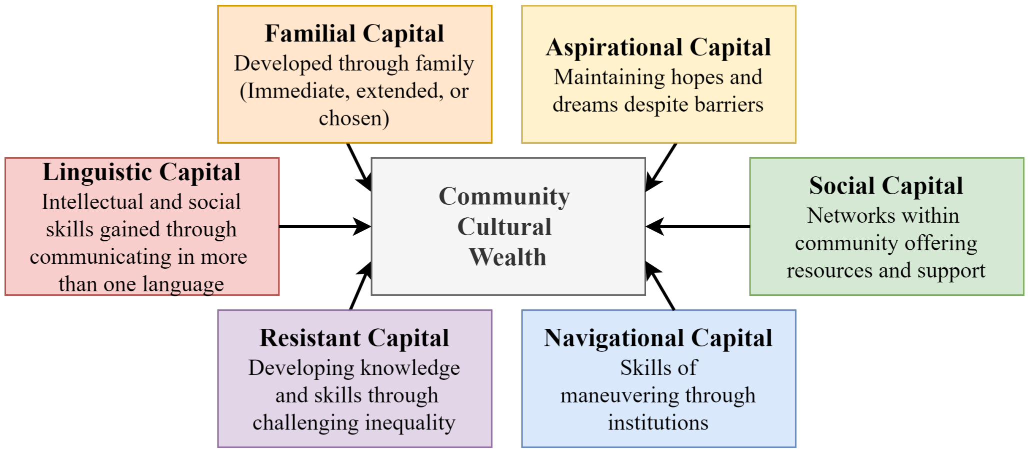


Figure 4.2: Overview of the community cultural wealth (CCW) model

Within the CCW framework, Yosso describes six interconnected forms of cultural capital as follows [Yosso, 2005]:

- *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 [Burt and Johnson, 2018, Denton et al., 2020, Rincón and Rodriguez, 2020, Ong et al., 2020, Lane and Id-Deen, 2020]. For example, peer support leverages aspirational capital and help minoritized populations "[...] to see themselves as STEM-engaged individuals and persist towards STEM careers" [Rincón and Rodriguez, 2020, p. 6]. Peer support can also tap into social capital, as students build a community and work together to study and to solve problems [Lane and Id-Deen, 2020]. 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.

4.5 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 4.5.1. Then we share the demographics for the population which completed the survey in Section 4.5.2. In Section 4.5.3, we discuss the data analysis.

4.5.1 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 Table 7.2 of the Appendix.

While the bulk of the questions were previously validated [Taheri et al., 2019], 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.

4.5.2 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 4.1. Then we detail the racial/ethnic affiliations in Table 4.2.

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 stu-

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 4.1: 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 4.2: Racial/ethnic identity of participants

dents. 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.

4.5.3 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 [Khalilzadeh and Tasci, 2017, Mangiafico, 2016]. Initially, descriptive statistics were collected. For further analysis, Shapiro-Wilk tests were run to evaluate the normality of the data [Shapiro and Wilk, 1965]. 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 [Mangiafico, 2016]. We also used Kruskal-Wallis tests, which are similar to the Wilcoxon rank-sum tests but are for more than two groups [Mangiafico, 2016], to examine the link between cultural experiences and preparation. Freeman's theta (θ) and epsilon-squared (ϵ^2) statistics were calculated to determine the effect size of statistically significant differences in how early preparation began, and the hours spent preparing [Khalilzadeh and Tasci, 2017, Mangiafico, 2016]. For effect sizes, we considered a small effect for ϵ^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 [Mangiafico, 2016]. For Freeman's θ, 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.

4.6 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 4.3). 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 4.3: Number of technical interviews students report, as percent of total students

4.6.1 C4RQ1: 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 4.6.1.1. In Section 4.6.1.2 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 4.6.1.3.

4.6.1.1 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 4.3, 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).

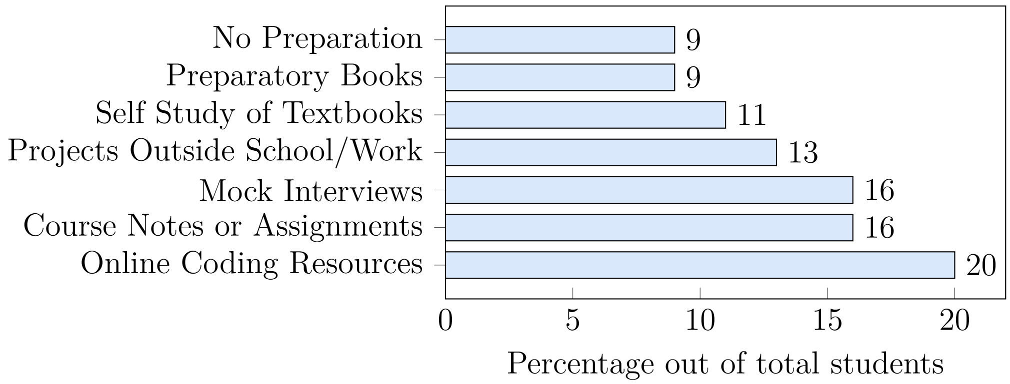
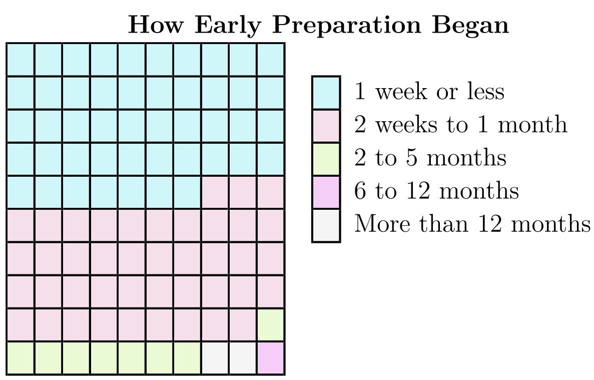


Figure 4.3: Resources utilized for technical interview preparation

4.6.1.2 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 4.4. 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.



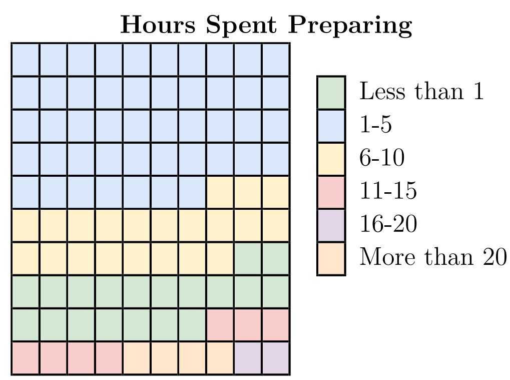


Figure 4.4: Breakdown of students' preparation for technical interviews, in terms of how early preparation began and the hours spent preparing, where each box represents 1%

4.6.1.3 How Personal Inputs may Impact Preparation

We considered how the preparation time spent may vary by gender, race, and ethnicity as shown in Table 4.4. 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.

4.6.2 C4RQ2: 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 4.6.2.1). Next, we compare the likelihood of different populations reporting certain cultural experiences in Section 4.6.2.2. Then in Section 4.6.2.3, we examine the impact of these cultural experiences on preparation time.

4.6.2.1 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

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

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 Table 7.2 of 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 4.5, the majority of students did report spending some duration working a job, whether computing related (54%) or non-computing related (58%). In addition, 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.

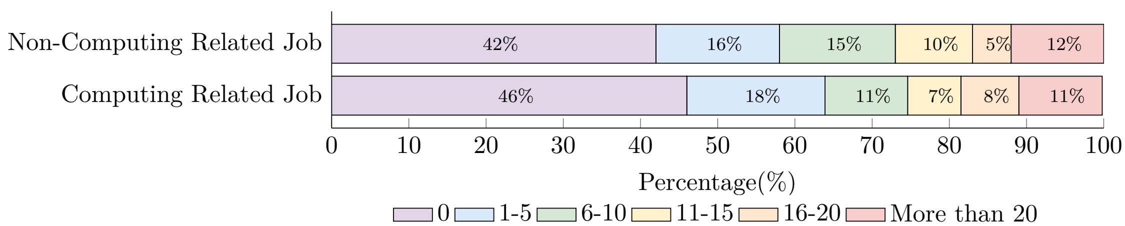


Figure 4.5: Hours students spend in computing and non-computing related jobs

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 4.6A), 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 4.6B. Most often, students reported that their home environment was extremely supportive (61.2%).

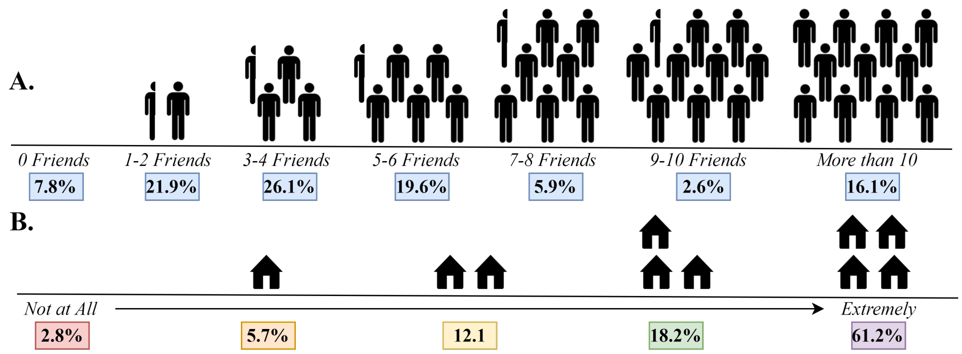


Figure 4.6: Number of friends students reported having in computing (A.), and how supportive their home environment is towards computing (B.)

4.6.2.2 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 [Garcia et al., 2018]. Therefore, to determine the impact of specific cultural experiences on different populations, we used Wilcoxon tests, as shown in Table 4.5.

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 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

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

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 ($p < .001$).

4.6.2.3 Impact of Cultural Experiences on Preparation

To explore the impact the specific cultural experiences previously described on preparation, we ran Kruskal-Wallis tests (Table 4.6). 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.

	How Early Preparation Began				*Hours Spent Preparing*			
Cultural Experience	***p*-value**	χ^2	ϵ^2	θ	***p*-value**	χ^2	ϵ^2	θ
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 4.6: Kruskal-Wallis tests to examine cultural experiences impact on preparation time

4.6.3 C4RQ3: 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 based solely on students that reported having at least one interview (or more). As shown in Table 4.7, 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 4.7: 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 4.8. 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.

Although the significance observed in females and White students suggested a link may exist between preparation and career attainment/outcomes, we wanted to

		Not Female	*Female*		*Not HL*	*HL*		*Not Black/ AA*	*Black/ AA*		*Not White*	*White*		*Not Asian*	*Asian*
Outcome	***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 4.8: Job offers, with significance levels and the means of each group

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 4.9, 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).

	# of Computing Job Offers				*Non-Computing Related Jobs*				*Computing Related Jobs*			
Preparation Time	**p-value**	χ^2	ϵ^2	θ	**p-value**	χ^2	ϵ^2	θ	**p-value**	χ^2	ϵ^2	θ
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 4.9: 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, 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 ϵ^2 and Freeman's θ. As a control, we also analyzed how 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.

4.7 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 [McDowell, 2015]. 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 4.4, 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 [Blaney, 2020]. 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 [Blaney and Stout, 2017, Blaney, 2020]. 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 [Carnevale and Smith, 2018], 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 4.6, time spent on non-computing jobs has a small effect (based on both the ϵ^2 and Freeman's θ) 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 [Lane and Id-Deen, 2020], 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 [Ahmed et al., 2013, Matturro, 2013, Radermacher et al., 2014, Sharma, 2014, Ford et al., 2017a, Garousi et al., 2019c, Oguz and Oguz, 2019, Gurcan and Sevik, 2019]. Therefore, multilingual students, or those who have previously served as interpreters in their own family [Ahmed et al., 2013, Trauth et al., 2012, Stevens and Norman, 2016], 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" [Lane and Id-Deen, 2020, 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 [Wu, 2009]. This computing control in turn results in stronger computer self-efficacy. While in general males are considered to have a higher computing affect [Liao, 1999, Whitley Jr, 1997], 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.

4.8 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 [Trauth et al., 2012, Ross et al., 2020, Mejias et al., 2019]. 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.

4.9 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 [Catolino et al., 2019, Vasilescu et al., 2015, Yarger et al., 2019]. 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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CHAPTER 5

IMPACT OF TECHNICAL INTERVIEWS, AND OTHER PROFESSIONAL AND CULTURAL EXPERIENCES ON COMPUTING IDENTITY

The goal of this chapter was to answer RQ3 of the dissertation: How do technical interviews, and other professional and cultural experiences impact computing identity? To evaluate students' experiences and to define computing identity for each student, quantitative analysis was performed using the same survey described in Chapter 4, although the focus is on different questions. The study presented in this chapter was already described in a publication that is in press [Lunn et al., 2021a].

5.1 Abstract

Increasingly companies assess a computing candidate's capabilities using technical interviews (TIs). Yet students struggle to code on demand, and there is already an insufficient amount of computing graduates to meet industry needs. Therefore, it is important to understand students' perceptions of TIs, and other professional experiences (e.g., computing jobs). We surveyed 740 undergraduate computing students at three universities to examine their experiences with the hiring process, as well as the impact of professional and cultural experiences (e.g., familial support) on computing identity. We considered the interactions between these experiences and social identity for groups underrepresented in computing —women, Black/African American, and Hispanic/Latinx students. Among other findings, we observed that students that did not have positive experiences with TIs had a reduced computing identity, but that facing discrimination during technical interviews had the opposite effect. Social support may play a role. Having friends in computing bolsters

computing identity for Hispanic/Latinx students, as does a supportive home environment for women. Also, freelance computing jobs increase computing identity for Black/African American students. Our findings are intended to raise awareness of the best way for educators to help diverse groups of students to succeed, and to inform them of the experiences that may influence students' engagement, resilience, and computing identity development.

5.2 Introduction

Companies looking to hire for computing positions frequently evaluate job candidates' technical proficiency using problem solving and coding tests [Behroozi et al., 2020a]. Although students may have completed coursework about the fundamentals of programming and algorithmic efficiency, answering these questions on the spot while also speaking their thought process aloud can be cognitively challenging and stressful [Behroozi et al., 2018, Behroozi et al., 2020b]. Technical interviews (TIs) are considered a major hurdle for students in computing looking to obtain a position in industry, and also for companies trying to grow and to build diverse teams [Behroozi et al., 2020a, Behroozi et al., 2020b]. Recent computer science graduates are often cited as lacking in technical abilities, communication skills, and other aspects of professionalism [Parker, 2018, Radermacher et al., 2014, Scaffidi, 2018b]. Given that there is already an insufficient amount of computing graduates to meet industry needs — and a dearth of women, Black/African American, and Hispanic/Latinx students — further deterring these populations at any stage is problematic [Rawlings-Goss, 2019a, Mandel and Carew, 2015, Echeverri-Carroll et al., 2018].

Certain experiences are considered beneficial to promoting disciplinary, racial, and academic identity [Varelas et al., 2012]. As such, it is important to consider how technical interviews, and other professional and cultural experiences, may impact students, and especially minoritized populations [Mandel and Carew, 2015, Whitney and Taylor, 2018, Behroozi et al., 2019, Behroozi et al., 2020a]. Previously **professional experiences** have been described as the "interactions, situations, and events individuals encounter while serving in a particular workplace role" [Klein, 2016, p. 3], and also include skill development (e.g., training/leadership opportunities), defining career goals, and/or networking [Worthen, 2005]. In this research, we extend the definition to include the hiring process, and specify the development of computing skills (e.g., participating in coding bootcamps or freelance computing-related jobs). Meanwhile, we define **cultural experiences** as the knowledge learned and shared, for which activities, behaviors, and the interpretation of experiences define everyday life [Adelman, 1988, McCurdy et al., 2004, Cultuur, 2014]. We consider items like day-to-day responsibilities (e.g., caring for others) and social support (in terms of home environment and peers).

Presently, it is unclear how professional and cultural experiences impact students' computing identity. **Computing identity** refers to the way that students perceive themselves with respect to computing fields (i.e., computer science (CS), computer engineering (CE), and information technology (IT)). Since students each have their own circumstances and pathways, it is also vital to consider the experiences of students with varying social identities.

Social identity refers to an individual's self-perception in relation to others [Garcia et al., 2020, Peters, 2018]. It includes race, ethnicity, gender, socio-economic status, sexual orientation, religion/spirituality, age, etc. [Garcia et al., 2020]. In our work, we focus solely on gender, race, and ethnicity.

This information can provide insight into ways to improve student engagement, resilience, and computing identity development, as well as learning about what may serve as supports or barriers for students looking to start their career. Such analysis is critical for exploring factors that may attract or repel groups already underrepresented in computing. To address this gap in the literature, we sought to answer the following chapter-specific research questions (denoted C5RQ#): **C5RQ1)** *What are the variations in students' experiences with technical interviews across different groups?*; **C5RQ2)** *How do technical interviews and other professional experiences impact computing identity?*; **C5RQ3)** *How do cultural experiences impact computing identity?*

5.3 Related Research

There is limited research on computing identity [Peters et al., 2014, Taheri et al., 2018, Taheri et al., 2019, Mahadeo et al., 2020], particularly in the context of underrepresented groups [Garcia et al., 2020, Rodriguez and Lehman, 2017, Rodriguez et al., 2020]. However, experiences and cultural goals (e.g., helping others) often play a role in aspects of computing identity such as sense of belonging [Lewis et al., 2019] and interest [Friend, 2016]. Literature has expressed the necessity of considering stereotypes and the impact of socialization on minoritized populations in computing [Rodriguez and Lehman, 2017, Rodriguez et al., 2020]. Inhospitable environments and marginalization can make it challenging for them to establish and maintain their computing identity [Garcia et al., 2020, Rodriguez and Lehman, 2017].

To this end, professional experiences have demonstrated an important role in computing students' development. Previously Kapoor and Gardner-McCune investigated professional identification with computing, and students long term career goals, and emphasized the necessity of schools offering activities to improve engagement and performance [Kapoor and Gardner-McCune, 2019]. They suggested that capstone courses, internships, and experiences such as hackathons can help with student development [Kapoor and Gardner-McCune, 2019, Parker, 2018].

While it is unclear how professional experiences with hiring affect student development (and retention in the field), whiteboard interviews have been described as a source of stress [Behroozi et al., 2018]. The hiring process in computing has been described as "leaky," and it is has been mentioned that current practices may discourage qualified candidates and underrepresented groups [Behroozi et al., 2020a, Behroozi et al., 2020b]. Behroozi et al. previously examined students ability to perform problem-solving of technical interview style questions in public and private settings [Behroozi et al., 2020b]. They detected that think-aloud procedures, and fear of being watched reduced performance. They also observed that while no women were able to successfully solve their problem in public, all were successful in private. They concluded that candidates responses may therefore not be related to problem-solving abilities but rather that "individual responses to stress and extraneous cognitive load can be driving hiring decisions instead of ability" [Behroozi et al., 2020b, p. 490].

In our work, we seek to understand self-reported positive and negative experiences with technical interviews, other professional experiences, and other cultural experiences students may have such as familial or peer support. We also disaggregate by race and gender, and consider the overall impact on computing identity.

5.4 Theoretical Framework

Identity theory considers the multi-dimensional and dynamic conceptualization of self, and the factors that contribute to its development [Kapoor and Gardner-McCune, 2019, Peters, 2018]. While many factors may influence a student's identity, in this work we focus on aspects of social identity and disciplinary identity. Disciplinary identity theory has been previously used to understand and evaluate persistence, and career choice in STEM fields [Carlone and Johnson, 2007, Hazari et al., 2010, Cass et al., 2011, Rodriguez et al., 2019, Godwin et al., 2016]. We focus on a specific type of disciplinary identity, computing identity, shown in Figure 5.1.

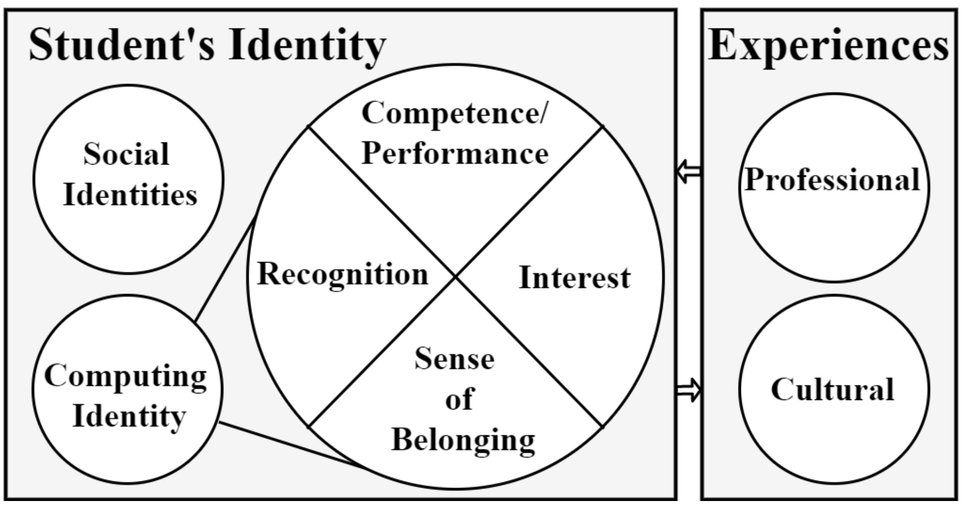

Figure 5.1: Student identity and experiences

Computing identity is conceptualized using the dimensions of interest, sense of belonging, recognition, and competence/performance [Taheri et al., 2018]. **Interest** is defined as a student's cognitive and affective engagement with respect to the subject matter (computing) [Taheri et al., 2019, Mahadeo et al., 2020]. **Sense of belonging** is defined as a student's feelings of support and their connection to the computing community [Taheri et al., 2018]. **Recognition** refers to a student's feelings of value and acknowledgement from others such as mentors, teachers, family, and friends [Taheri et al., 2019, Mahadeo et al., 2020]. **Competence/performance** is defined as a student's self-confidence in understanding computing and feeling accomplished in that topic. While the components are separate, they often interact and overlap based on context and population [Mahadeo et al., 2020].

Scholars have argued social identity is a valid basis for understanding student reflection and their interpretation of engagement in computing fields [Peters, 2018]. Also, computing professional identity has been examined in terms of how students develop as professionals within their major and in the field. Previously, Kapoor and Gardner-McCune (2019) used James Marcia's Identity Status Theory to describe how social, personal, and cultural identity can influence professional identity development in computing [Kapoor and Gardner-McCune, 2019]. They found that typically CS undergraduates form their computing professional identity between year 2 and 3 of their degrees, and that prior to this time, students may explore computing professions without being committed. It is suggested this relates to a lack of experience, doubts about technical competency, and/or indecisiveness. They stress the importance of educational environments that help to students obtain technical skills and knowledge, while supporting engagement in the community to build computing professional identity. As such, we seek to examine the impact of TIs, and other professional and cultural experiences on computing identity, for students from different backgrounds.

5.5 Methods

5.5.1 Survey Development and Administration

To analyze students' technical interview, professional, and cultural experiences, and their impact on computing identity, we leveraged a survey instrument. We used questions previously validated on STEM identity [Hazari et al., 2010, Cass et al., 2011, Taheri et al., 2018], to ensure our construct included reliable and accurate measures. Apart from inquiring about demographic information, items included asking about students' academic standing (year in school, major, and GPA), and inquiries into the students' educational history, home life, persistence, interests, and experiences. Questions were also added about the hiring process in computing, resulting in a total of 46 questions.

Since we included questions about hiring not previously assessed, a pilot study was conducted as well. As part of the pilot, we confirmed the questions were clear and matched the target topics, and that the experiences described were applicable to computing students. The survey was administered at three metropolitan universities in the United States, to undergraduate computing students (CS, CE, and IT majors), after Institutional Review Board approval.

5.5.2 Demographics

Our sample was an $n = 740$, of which 23.0% were female, 74.9% were male, and 2.1% reported as either transgender, agender, or a gender not listed. Racial/ethnic group affiliation of the students were: 42.2% White, 8.4% Black or African American, 14.9% Asian, 1.1% Native Hawaiian or Pacific Islander, 0.4% American Indian or Alaskan Native, 32.7% were Hispanic, Latinx, or Spanish origin, 2.4% Middle

Eastern or North African, and 1.6% another race or ethnicity not listed. For year in college, 6.8% of students were in their 1^{st} year, 9.5% were in their 2^{nd} year, 18.5% were in their 3^{rd} year, 43.4% were in their 4^{th} year, and 21.8% were past the 4^{th} year.

5.5.3 Analytics

We used R (version 3.6.1) to clean and analyze the data. Statistical analyses consisted of descriptive statistics, Wilcoxon rank-sum tests, confirmatory factor analysis (CFA), and regression analysis. For descriptive statistics and the interaction analysis, we focused on the underrepresented minorities of women, Hispanic/Latinx, and Black/African American students. Although the questions pertaining to computing identity were the same as the work previously conducted [Taheri et al., 2018], since this survey was administered in another year, with a different population, we performed CFA.

CFA was run to confirm that particular questions mapped onto the theorized computing identity sub-constructs [Brown, 2015]. The resulting latent variables for the sub-constructs were defined by the questions (indicator variables) denoted in Table 5.1. These items were averaged to create proxies for each sub-construct, and these were combined to represent an overall proxy measure for computing identity. All of the standardized factor loadings are above the accepted 0.6 threshold [Cabrera-Nguyen, 2010]. Although our χ^2 was significant ($p < 0.001$), since our sample was so large, we considered other fit indices to evaluate our model as well (presented below) [Brown, 2015].

The Root Mean Square Error of Approximation was 0.079, which is less than 0.08, and implies an "acceptable fit" [Rosseel, 2014]. The Comparative Fit Index was

Latent Variables	Indicator Variables	Standardized Factor Loading	SE	R^2 - Item Reliability	Construct Reliability	Average Variance Extracted
Recognition	Extent your family sees you as an exemplary student in computing fields	0.68***	0	0.46	0.83	0.63
	Extent other students see you as an exemplary student in computing fields	0.86***	0	0.74		
	Extent your teachers see you as an exemplary student in computing fields	0.83***	0	0.68		
Interest	Topics in computing excite my curiosity	0.87***	0	0.75	0.90	0.70
	Computer programming is interesting to me	0.70***	0	0.50		
	I enjoy learning about computing	0.93***	0	0.86		
	I like to know what is going on in computing	0.83***	0	0.68		
Competence/ Performance	I am confident I can understand computing	0.82***	0	0.67	0.80	0.57
	I can do well on computing tasks (e.g. Programming and setting up servers)	0.73***	0	0.53		
	I understand concepts underlying computer processes	0.71***	0	0.51		
Sense of Belonging	With respect to the computing community, to what extent do you feel part of the community	0.81***	0	0.65	0.89	0.68
	With respect to the computing community, to what extent do you feel feel valued and respected	0.85***	0	0.72		
	With respect to the computing community, to what extent do you feel you can share	0.80***	0	0.65		
	With respect to the computing community, to what extent do you feel you can be heard	0.84***	0	0.70		

***p < .001

Table 5.1: Computing identity construct factor loadings

0.952, which is above the threshold for a good model fit ($\geq$0.95), and indicates that 95.2% of the co-variation in the data can be reproduced by our model [Gatignon, 2010]. Likewise, the Relative Fit Index (0.924), Normed Fit Index (0.942), and Non-Normed Fit Index (0.937), were all above the "good fit" threshold as well. Contrarily, for the Standardized Root Mean Square Residual (SRMR), the smaller the value, the better the fit, and a value of 0 suggests a "perfect fit." In our analysis, the model's SRMR was 0.043, which is less than the 0.05 threshold required to denote a "good fit."

Regression is a statistical method used to establish relationships between a dependent variable and one (or more) independent variable(s), and to explore their interactions [Harrell Jr, 2015]. Specifically we examined how TIs, cultural, and professional experiences predict computing identity. The precise professional experience questions (PEQ) and cultural experience questions (CEQ), and their responses, analyzed in the regression model are shown in Table 5.2. The final regression model was built using backwards block elimination [Harrell Jr, 2015].

5.6 Results

5.6.1 Technical Interview Experiences (C5RQ1)

To answer C5RQ1 about the variations in students' experiences with technical interviews across different groups, we first examined how many TIs different groups had (PEQ2), and the number of job offers received (PEQ5), as shown in Table 5.3. The number of job offers was only calculated for students that reported having at least one technical interview ($n = 350$). Percentages were calculated as the representation relative to others within the group.

Professional Experiences	
Professional Experience Questions (PEQ)	**Responses**
PEQ1: Which of the following professional experiences, if any, have you had at your institution with respect to computing? Mark all that apply.	Industry Internship; Research experience; Shadowing experience; Part time or full time job in computing; Mock interviews; Personal computing projects, outside of normal classwork; Freelance computing-related jobs; Hackathons/Programming competitions; Certifications (e.g. CompTIA A+, IT Infrastructure Library (ITIL), Tableau, Project Management, Google Cloud); Coding bootcamps; Networking with industry and other professionals; Attending symposia, conferences, or other computing events; ePortfolio, digital portfolio, or personal website
PEQ2: How many programming or technical job interviews have you completed in computing?	0; 1-2; 3-4; 5-6; 7-8; 9 or more
PEQ3: Which of the following apply to your positive experience(s) with technical interviews. Mark all that apply.	I have NOT had positive experiences; really prepared; the questions asked were relevant for the position; the questions asked were easy; the interviewer treated me like an equal; the interviewer guided me (with hints/help); the interviewer was kind and/or respectful; Other
PEQ4: Which of the following apply to your negative experience(s) with technical interviews. Mark all that apply.	I have NOT had negative experiences; like I was not prepared; the questions were not relevant for the position; the questions asked were too difficult; the interviewer treated me like I was inferior; the interviewer did not provide any guidance; the interviewer was harsh and/or critical; discriminated against; Other
PEQ5: How many job offers have you received in computing?	0; 1; 2; 3; 4; 5 or more
PEQ6: 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
Cultural Experiences	
Cultural Experience Questions (CEQ)	**Responses**
CEQ1: How supportive is your home environment towards computing?	5-point Likert scale: Not at all supportive to Extremely supportive
CEQ2: How many friends do you have in computing programs?	0; 1-2; 3-4; 5-6; 7-8; 9-10; More than 10
CEQ3: 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); Caring for an adult (e.g. grandparent); Personal recurring health problem (not including common illnesses like a cold or flu); Other

Table 5.2: Experiential items assessed

Number of Technical Interviews				
Group	**0**	**1 or More**	**M**	**SD**
Male	50.00%	50.00%	1.49	2.21
Female	47.68%	52.32%	1.78	2.55
Asian	51.82%	48.18%	1.78	2.68
Black or African American	48.39%	51.61%	1.60	2.23
Hispanic/Latinx	53.31%	46.69%	1.47	2.35
White	45.51%	54.49%	1.48	2.02
All Students	48.00%	52.00%	1.44	2.22
Number of Job Offers				
Group	**0**	**1 or More**	**M**	**SD**
Male	59.15%	40.85%	0.80	1.25
Female	52.98%	47.02%	1.02	1.51
Asian	60.00%	40.00%	0.84	1.30
Black or African American	62.90%	37.10%	0.77	1.17
Hispanic/Latinx	58.68%	41.32%	0.79	1.29
White	53.53%	46.47%	0.92	1.33
All Students	62.00%	38.00%	0.76	1.25

Table 5.3: Technical interviews and job offers, as percentages of total students in sample, means, and standard deviations

We observed that the majority of students (52.0%) have had at least one technical interview. However, there were variations in the quantity of TIs different groups reported. According to a Wilcoxon rank-sum test, White students had more TIs on average than non-White students ($p = .016$), and received more job offers ($p < .001$). Overall, the majority of students (White students included) did not receive any job offers after their TIs (62.00%). Yet there was a significant effect for gender and, as confirmed by a Wilcoxon rank-sum test (at $p = .008$), females received more job offers on average. We also used regression to verify that the number of TIs was predictive of the number of job offers received ($p < .001$).

Next we examined which experience(s) students reported during TIs, for students who had one or more TIs. These responses are valuable given the large number of students that completed at least one technical interview. Only 9.43% of students reported they did not have positive experiences, but 34.86% reported they did not have negative experiences. The top five most common positive experiences (PEQ3) selected by students during technical interviews were: 1) "The interviewer was kind and/or respectful," 60.29%; 2) "The questions asked were relevant for the position," 56.86%; 3) "The interviewer treated me like an equal," 43.43%; 4) "The interviewer guided me (with hints/help)," 32.86%; 5) Feeling "Really prepared," 26.29%. The top five most common negative experiences (PEQ4) for students during technical interviews were: 1) Feeling "Like I was not prepared," 31.14%; 2) "The questions asked were too difficult," 18.00%; 3) "The questions were not relevant for the position," 16.86%; 4) "The interviewer did not provide any guidance," 12.57%; 5) "The interviewer treated me like I was inferior," 11.14%.

5.6.2 Impact of Experiences on Computing Identity (C5RQ2 and C5RQ3)

We used regression to examine the impact of technical interviews and other professional experiences on computing identity (C5RQ2), as well as evaluating cultural experiences on computing identity (C5RQ3). As shown in Table 5.4, we first controlled for demographics and background variables not directly associated with undergraduate computing experiences to minimize the effect of confounding variables, and then to estimate the effects of our factors of undergraduate computing experiences more "purely" [Harrell Jr, 2015]. Block I shows the control set of variables, and then in Block II we added in the experiential variables to explore the role of each, as well as interaction effects with gender and race/ethnicity. It should be emphasized that although we present the control variables, experiential variables, and the interactions as distinct sections in Block II, the model itself was analyzed together. The cultural and professional experiential variables with a significant effect on computing identity pertain to the entire population, whereas the interactions focus solely on marginalized populations (females, Black/African American, and Hispanic/Latinx students). We observed that the adjusted R^2 for our control block was 10.25%, and with the addition of experiential variables, rose to 24.24%. This denotes a 13.99% gain in the variance explained from the experiential variables that were added.

Correlated predictors can cause an issue known as multicollinearity [Kock and Lynn, 2012]. To determine if this was an issue, we ran variance inflation factor statistics on our models. Typically the threshold is greater than 3.3 [Cenfetelli and Bassellier, 2009]. However, for all the variables, all the statistics were less than 1.5, suggesting that multicollinearity is not a substantial issue in our model.

	I				*II*			
Parameters	**Estimate**	**Sig.**	**SE**	β	**Estimate**	**Sig.**	**SE**	β
Control Variables								
(Intercept)	1.82	***	0.22	.00	1.94	***	0.21	.00
Institution (2)	0.09	ns	0.06	.07	-0.01	ns	0.05	-.01
Institution (3)	0.11	ns	0.07	.07	0.08	ns	0.06	.05
Majoring in CS	-0.03	ns	0.06	-.03	-0.02	ns	0.06	-.02
Majoring in IT	-0.13	ns	0.07	-.08	-0.15	*	0.07	-.10
Other Major	-0.44	***	0.09	-.20	-0.36	***	0.09	-.16
GPA in Computing	0.29	***	0.06	.18	0.22	***	0.06	.14
Grade in College Math	0.04	ns	0.04	.04	0.04	ns	0.03	.05
Black/African American	-0.11	ns	0.08	-.05	-0.21	**	0.08	-.09
Hispanic/Latinx	0.13	**	0.05	.10	-0.11	ns	0.08	-.08
Female	-0.23	***	0.05	-.15	-0.68	***	0.14	-.44
Hours Working Non-Computing Job	0.00	ns	0.00	.03	0.00	ns	0.00	.02
Experiential Variables								
Hours Working Computing Job					0.01	**	0.00	.10
Personal Computing Project Outside Classwork					0.09	*	0.04	.07
Freelance Computing Jobs					0.21	*	0.08	.09
I have NOT had positive experiences with TI					-0.29	**	0.10	-.10
Really Prepared for TI					0.28	***	0.06	.15
Discriminated Against in TI					0.79	**	0.28	.09
Supportive Home Environment					0.01	ns	0.02	.03
Friends in Computing					0.01	ns	0.01	.04
Interactions								
Female *and* Supportive Home Environment					0.15	***	0.04	.34
Hispanic/Latinx *and* Friends in Computing					0.03	**	0.01	.16
Black/African American *and* Freelance Computing Jobs					0.58	*	0.27	.08

*p < .05; **p < .01; ***p < .001; *Note.* ns = not significant; TI = technical interviews

Table 5.4: Regression model predicting computing identity measure with interactions

5.7 Discussion

The majority of computing students reported having TIs (52.00%). Overall, it is encouraging that only 9.43% reported not having any positive experiences. However, the negative experiences encountered demonstrate that there is still room for improvement from students, educators and institutions, and industry. The top negative experience reported was that students felt unprepared. While to some extent students are responsible for remedying this, universities could help to make students aware of what to expect early in their education, suggesting resources (e.g., LeetCode) and offering increased opportunities to prepare (e.g., mock interviews). They could also offer more examples in courses to expand students' familiarity with different problems, and the application of theory.

In terms of the regression, several of the relationships between professional experiences and computing identity were unsurprising. Students that felt really prepared for TIs had a higher computing identity (β = .15), and those students that did not have positive experiences with TIs had a lower computing identity (β = -.10). Also, hours spent working in a computing job (β = .10), or completing personal computing projects outside of classwork (β = .07) also positively predicted computing identity. While freelance computing jobs improved computing identity for all students (β = .09), there was a notable positive interaction for Black/African American students (β = .08). We posit encouraging computing students to seek out such opportunities or facilitating such latitude may provide students an additional space to showcase their skills, which may contribute to aspects of computing identity like performance and confidence. This aligns with literature that professional experiences can help with student development and performance [Kapoor and Gardner-McCune, 2019]. However, since freelance jobs allow students to be selective, they may also choose to only take on projects that appeal to them, which may impact their interest as well. Offering students opportunities to take on freelance projects may be a great way to encourage participation in the field, without the rigor and stress associated with TIs. If universities are not presently including such options through their career services, seeking out partnerships with industry, and developing these opportunities for students could be a great way to add value and encourage development of computing identity.

What was notable in the regression model is that being discriminated against during TIs actually had a positive impact on computing identity ($\beta = .09$). Also, all of the students reporting this experience did belong to groups considered underrepresented in computing. Typically discrimination and bias experiences are considered negative for students, and often result in a diminished sense of belonging and retention for students of color [Hussain and Jones, 2019, Hurtado and Ruiz Alvarado, 2015]. As such, we further explored which aspects of computing identity were impacted by being discriminated against during TIs. In the new model, we made being discriminated against a predictor for combined measure of computing identity and it yielded an estimate 0.87 ($\beta = 0.10$). Comparatively, the estimate for being discriminated against in predicting sense of belonging alone was 1.24 ($\beta = .10$). In terms of the other sub-constructs — the estimate for recognition was 0.79 ($\beta = .07$), it was 0.90 ($\beta = .08$) for competence and performance, and interest was not significant. This confirmed that being discriminated against during a professional experience had the biggest impact on sense of belonging, extending prior literature about sense of belonging to an institution [Hussain and Jones, 2019]. Accordingly, we hypothesize these discriminatory experiences may have actually encouraged students to persevere in computing, and rather than deterring them, it pushed them to work harder to succeed [Duckworth et al., 2007].

Positive social experiences with supportive individuals play an important role in persistence and development of self-efficacy for minoritized students in STEM fields [Hall et al., 2017]. In addition, ethnically diverse friends and classrooms can provide additional support to bolster resistance in the face of discrimination [Hall et al., 2017, Hussain and Jones, 2019]. While there were no significant gender or racial/ethnic interactions for discrimination during TIs, we did observe a significant interaction for Hispanic/Latinx students and the number of friends in computing ($\beta = .16$), which led to an improved computing identity. Furthermore, there was a significant interaction effect for females and a supportive home environment ($\beta = .34$). Given that on average females received more job offers than males, the impact of cultural experiences in providing positive support should be considered.

While we have focused on the significant experiences described, we would also like to draw attention to some of those that were not, from the full list examined in Table 5.2. The absence of certain experiences makes a compelling case that these items could be reworked or redesigned to maximize their benefit to computing students. For example, while the hours spent working in a computing job did predict computing identity, shadowing experience did not. Therefore, it may be less important to observe others, and more meaningful to perform computing in a professional capacity. This aligns with prior work in STEM which demonstrated students prefer learning via hands-on material to abstract material (i.e., concepts, theories) [Kulturel-Konak et al., 2011]. Students in computing have also been shown to have a more positive self-image when applying exploratory problem solving, and finding their own solutions to problems [Schulte and Knobelsdorf, 2007]. Thus, the way shadowing opportunities are presently structured may need refinement. Future research could investigate more effective ways of setting up such experiences. Additionally, although qualitative research has suggested informal activities like hackathons/programming competitions may help computing students to meet others, and may be influential in career choices [Kapoor and Gardner-McCune, 2019], they did not predict computing identity. As such, their impact on computing identity may be less overt and instead mediated through aspects such as serving to reinforce skill development.

In summation, based on the findings we suggest institutions implement the following: 1) Raise awareness of the expectations of TIs early in students' education, suggesting resources to prepare, and offering mock interviews and other training.; 2) Provide more examples in coursework to familiarize students with the ways theoretical concepts can be applied.; 3) Consider industry partnerships to offer freelance opportunities, which can increase hands-on experience and help students apply conceptual knowledge.; 4) Consider reevaluating the curriculum to build in space and latitude for co-ops or internships throughout their computing education; 5) Promote organizations/groups which may provide support for minoritized populations, and offer socialization opportunities within the department to help students build a peer network.

5.8 Limitations

The findings from our investigation are limited in several ways. First, sample sizes related to underrepresented groups in computing will always be an issue until representation meets parity. Thus, in order to increase confidence in the results, further studies will be necessary. Moreover, we do not consider the intersectionality of the different groups here. This may limit our understanding of relationships of differential importance for intersecting identities. While this was beyond the scope of the current work, it would be worthwhile to consider as it could provide more nuanced insight into the perceptions and experiences of students.

Also, we only employ quantitative analysis. While this may provide numerical confirmation of the effects observed, we cannot be certain about what the observed relationships mean without further examination. Particularly when exploring the discrimination faced during TIs, going forward, it would be valuable to develop an in depth qualitative understanding of students' experiences.

5.9 Conclusions

The current inquiry provides empirical evidence of the impact of TIs on students. It also demonstrates that individual professional and cultural experiences play an important role in predicting computing identity. We suggested ideas institutions could implement to help students bolster computing identity, and to persevere in TIs. By exploring the experiences that affect computing identity for different groups, we seek to emphasize the importance of not treating all students as a monolith, and offering diverse opportunities and options to engage and encourage students. In the future, qualitative exploration could result in additional insight into the nuances of the relationships described in this work.

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CHAPTER 6

STUDENTS' EXPERIENCES WITH TECHNICAL INTERVIEWS

The purpose of this chapter was to answer RQ4 of the dissertation: How do students describe their experiences with the hiring process in computing? In order to achieve this, phenomenography was employed to explore the qualitatively different ways that undergraduate students in computing fields from different gender, racial, and ethnic groups experience technical interviews and their pathways to a career. This study uses the theoretical frameworks of identity, intersectionality, and community cultural wealth to explore undergraduate computing students perceptions of the hiring process, with a focus on underrepresented populations, and to better understand barriers technical interviews pose to job attainment. In addition, this chapter identifies solutions to improve student preparation and hiring.

6.1 Introduction

To better understand students' experiences with technical interviews, and to situate this knowledge within the larger context of hiring and career pathways, I performed a qualitative analysis. In particular, I focused on job attainment in computing for Black/African American, Hispanic/Latinx, Asian, and mixed-race men and women. In this chapter, I first described the research questions that guided this work in Section 6.2. Then, I provide background information on the qualitative methodology I employ throughout this research, phenomenography. Then I describe the theoretical frameworks that shaped this inquiry — identity theory, intersectionality, and community cultural wealth (CCW) — in Section 6.4. In Section 6.5 I delve further into the methods employed including participants, the semi-structured interviews, and data analysis. The positionality of the authors are addressed in Section 6.6. The outcome spaces that emerged from this inquiry are presented in Section 6.7, and then the implications of the results are discussed in Section 6.8. Next, the validity and reliability of this work is covered in Section 6.9, and limitations are described in Section 6.10. Finally, I present the conclusions of this study in Section 6.11.

6.2 Research Questions

This research study uses the theoretical frameworks of identity, intersectionality, and community cultural wealth to explore the experiences of underrepresented undergraduate computing students and the hiring process, to better understand the barrier of technical interviews to job attainment. This investigation was guided by the following chapter-specific research questions (denoted C6RQ#):

- **C6RQ1:** How do students leverage the cultural capital associated with their self-identified racial, ethnic, and/or gender identity to obtain a job in computing?
- **C6RQ2**: What do students feel would help to improve hiring in computing?

6.3 Background

In this section, I provide background on technical interviews, and the methodology I use to explore them. First, a description on of phenomenography is provided in Section 6.3.1. Then, major developments in phenomenography over time are discussed in Section 6.3.2.

6.3.1 What is Phenomenography?

Phenomenography has been widely employed to assess the relationships between participants' and their conceptualizations of phenomena [Boustedt, 2008, Felix, 2009, Bucks and Oakes, 2011, Kinnunen and Simon, 2012b, Salzman, 2014, Peters et al., 2014, Dringenberg, 2015, Gandhi-Lee et al., 2017, Peters, 2018, Grande et al., 2018, Smith, 2015]. Understanding arises simultaneously from reflection within each individual, as well as ascertaining the similarities and differences of collective experiences across groups of individuals to maximize variation in the ways experiences are felt and described [Booth, 1997, Berglund, 2004, Boustedt, 2008, Bucks and Oakes, 2011, Kinnunen and Simon, 2012b]. Ontologically, phenomenography considers phenomena as shaped by the experiences of those engaging in it themselves and their perceptions of reality [Han and Ellis, 2019]. According to Bowden, there are four distinct stages in phenomenographic research including planning, data collection, analysis, and interpretation [Bowden, 2000]. However, data analysis is often described using varying levels of granularity, and may include merely identification, sorting, contrasting and categorizing, and reliability checking, or additional phases such as familiarization, condensation, or grouping [Han and Ellis, 2019].

Although I acknowledge there may be different approaches [Han and Ellis, 2019], a broad overview of the phases in phenomenography are shown in Figure 6.1, synthesized from scholars in the field [Marton and Booth, 1997, Säljö, 1997, Bowden, 2000, Bowden et al., 2005b, Daly et al., 2012]. As is common in academia, first a problem is identified, the purpose articulated, research questions developed, and methodology is selected (A). Once phenomenography has been chosen, it is important to determine who will be assessed, how this will be carried out, and to justify these choices in relation to the purpose (B). Then, participants or subjects are identified and recruited (C). Data are gathered next, whether using observation, in-

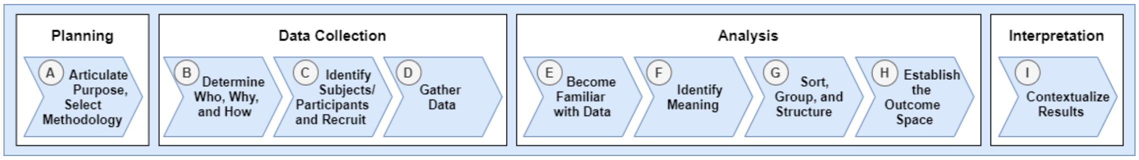

Figure 6.1: Stages of phenomenography

terviews, or open ended-questionnaires (D). While the precise analysis process may vary by intended outcome, in general, it entails familiarization with the data (E), identification of meaning (F), sorting, grouping, and structuring of the experiences (G), and establishing the outcome space (H). The outcome space requires a categorical description and accompanying illustrative statements [Marton, 1994, Bowden, 2000]. Also, it may be represented using tables, diagrams, or figures [Yates et al., 2012]. Once the outcome space is finalized, the results are contextualized and described (I).

6.3.2 Developments in Phenomenography

The earliest research described as "phenomenographic" pertains to work conducted in the 1970s, and first appearing in a publication in 1981, by a group at the University of Gothenburg in Sweden under the guidance of Ference Marton [Marton, 1981, Marton, 1986]. They sought to pragmatically assess "conceptions of various aspects of reality as the superordinate categories" [Marton, 1981, p. 189] to explore how variations in experiences result in differing learning outcomes in education [Larsson and Holmström, 2007, Salzman, 2014]. Marton's approach to analysis utilizes decontextualized excerpts which comprise a "pool of meanings" [Marton, 1986]. The researcher then collects and sorts the quotes into cohesive categories, considering the dimensions of variation among the meanings.

As further disciples of the Swedish or "Gothenburg phenomenography," Hasselgren and Beach argue there are five distinct contexts of phenomenography: experimental, discursive, naturalistic, hermeneutic, and phenomenological [Hasselgren and Beach, 1997, p. 197]. *Experimental phenomenography* focuses on learning outcomes, and understanding how students approach tasks. Phenomenographically, the outcome space is defined as "the qualitatively different ways of understanding the same phenomenon." Meanwhile, *discursive phenomenography* is related to Marton's description of "pure" phenomenography (although the authors argue there is no such thing), and considers discourse to provide "a collection of variegated and pragmatic responses to the demands of investigating a particular kind of research object under different conditions" [Hasselgren and Beach, 1997, p. 197]. *Naturalistic phenomenography* takes an observational approach, without the researcher manipulating or interacting with the participants, and merely observing their interactions. Then phenomenography is employed in the analysis based on what was said or the actions seen. Meanwhile, in *hermeneutic phenomenography* the analysis is focused on exegesis, critical explanation or interpretation of literary or written text. Finally, *phenomenological phenomenography* considers the social and contextual nature of a study to understand the essence of the experiences involved. This variant necessitates exploration of the dissimilitude and overlap between phenemenology and phenomenography.

For clarification, I want to emphasize that although both phenomenography and phenomenology seek to understand experiences of phenomena, their focus, outcomes, and uses are distinct [Larsson and Holmström, 2007, Beagon, 2021]. Phenomenography addresses research that aims to describe the *variation* or different ways a group of people experience a phenomenon, whereas phenomenology seeks to clarify the phenomenon's structure and meaning, seeking *common* perspectives from a group of people [Larsson and Holmström, 2007]. Hasselgren and Beach (1997) argue that some early work may have been misclassified due to a lack of the formal label of phenomenography at the time. Instead, they posit that "most phenomenographers tend to view the descriptions of outcomes of learning as the phenomenographic enterprise, phenomenological criteria concern questions directed toward the essences of experiences, for instance experiences of learning" [Hasselgren and Beach, 1997, p. 199].

Researchers often distinguish between Marton's approach to pure phenomenography (also referred to as original or "new" [Cummings, 2015, Mendoza Garcia, 2016]) and an approach defined by Australian researcher John Bowden, "developmental phenomenography" [Bowden et al., 2005a]. Bowden considers practical applications and the use of outcome spaces. Rather than focusing on individual quotes, Bowden considers whole transcripts, which are grouped based to maintain their context on the entirety of the interview [Bowden, 2000]. The researcher then seeks shared meanings amongst the "different things." Although other styles and variations later emerged, given the foundational contributions of these two disparate approaches, I present a broad comparison in Table 6.1. Researchers may also employ a combination of Marton and Bowden's approaches towards phenomenography [Smith, 2015, Mendoza Garcia, 2016], selecting aspects of each where appropriate in their context.

My investigation examined the juxtaposition of logical consistencies among students' interpretations of the hiring process in computing (the phenomena) with incongruities in how applicants from specific collectives, based on race, ethnicity, and gender, perceive the hiring process. In alignment with the contexts described by Hasselgren and Beach [Hasselgren and Beach, 1997], rather than describing this approach as "new" phenomenography, the methodology I employed in this disserta-

	Original, Pure, or “New” Phenomenography: Marton (Sweden)	**Developmental Phenomenography: Bowden (Australia)**
Goal	Experiencing the phenomenon is described by a set of critical aspects/features that a learner is able to “discern,” “be aware of,” or “focus on” simultaneously	Research is designed with the intention that there will be practical outcomes, and aims to enable others to change their own experiences
Data Collection	Varied conceptions participants have about “same things”	Participants discuss “different things”
Data Analysis: Become Familiar with Data	Necessary; Analysis reliability checked by coding of independent researchers	Necessary; Analysis performed by team of researchers
Data Analysis: Identify Meaning	Quotes/excerpts selected to create a “pool of meanings”	Using whole transcripts, sections are considered “in situ”
Data Analysis: Sort, Group, and Structure	Ways of dealing with the task; Look for variation in the meanings of the ”same thing”	Aims to create developmental outcomes to enable others to change their own experiences
Data Analysis: Establish the Outcome Space	Search for dimensions of variation in the pool of quotes, related in a hierarchy from less to more complex	Transcripts sorted in groups from less to most powerful; Structural links between categories investigated after the categories already determined

Table 6.1: Comparison of Marton and Bowden’s phenomenographic approaches

tion, which guided the procedures for data collection and analysis, was “discursive phenomenography.” In this inquiry, the pool of meanings approach was used since the participants often jumped around in their description of specific interviews to mention other encounters and experiences. In addition, as students became more adept at interviewing for jobs, the way they discussed their encounters also varied.

6.4 Theoretical Frameworks

For this research, three frameworks were used — identity theory (described in Section 6.4.1), intersectionality (described in Section 6.4.2), and community cultural wealth (described in Section 6.4.3). I drew on the knowledge and understanding within the community, and the capital that individuals offer to computing, as well as how their own identities contribute to their academic, programmatic, cultural, and professional experiences. To achieve this, I selected CCW, in addition to identity theory, giving consideration to both computing identity and aspects of social identity, such as race, ethnicity, gender, and role, also considering how intersectionality shapes experiences as described in Figure 6.2. The chosen theoretical frameworks were utilized throughout the development of the research question and interview protocol, they informed the selection of methodology (phenomenography) and participants, and they were applied during interpretation of the findings. A further description of how theoretical frameworks are applied in phenomenography is discussed in Section 6.4.4.

6.4.1 Identity

A complete description of identity, in terms of its broad conceptualization, along with definitions of social identity, role identity, disciplinary identity, and computing

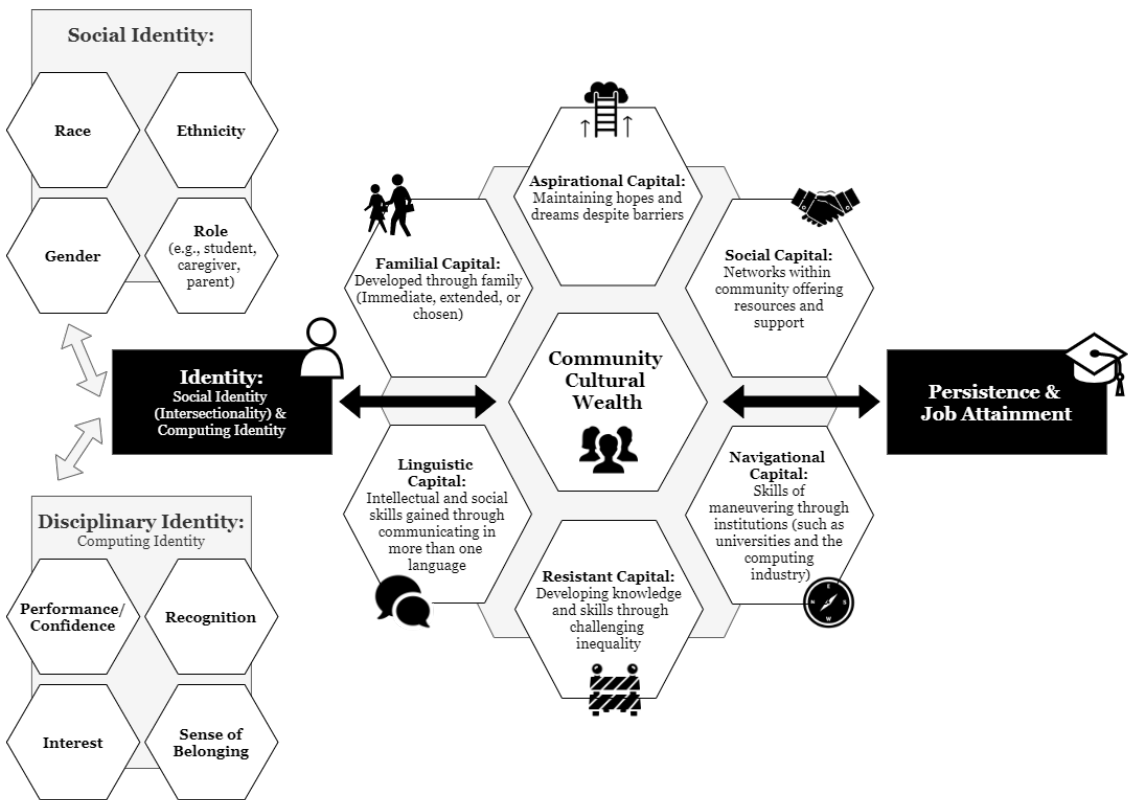

Figure 6.2: Framework of factors influencing persistence and job attainment in computing, including aspects of social and disciplinary identity and the community cultural wealth model

identity are provided in Section 2.1 of Chapter 2. In this chapter, I focused on social identity, in regards to how students identified with a particular gender, or with different racial/ethnic group(s). Social identity was considered when selecting participants, since obtaining a diverse population is tantamount to phenomenography, and I wanted to focus on the experiences of populations underrepresented in computing. I also examined computing identity, and used it when defining the interview protocol (see script in the Appendix), and during interpretation of the results on how students' pathways to a career may be influenced by sub-components such as interest (described further in Section 6.8). In addition, I considered how technical interviews may impact their feelings of being a computing person. Enmeshed within the concept of social identity is a related but unique concept described as intersectionality.

6.4.2 Intersectionality

In this chapter, intersectionality was used to explore students' pathways to a career in computing, particularly considering men and women of color. Within the findings and interpretation, I also considered the counterspaces these students relied on to deal with instances of racism and/or sexism. The concept of intersectionality, and the importance of counterspaces, are defined and described further in Section 2.2 of Chapter 2. Intersectionality played a vital role in the phenomenographic inquiry. It shaped planning and design, data collection (in terms of participant selection and development of the interview protocol), and interpretation of the results. Yet due to the nature of the qualitative methodology chosen, it was not involved with the analysis phase (since the categories are meant to emerge from the data itself without the influence of a theoretical framework).

Given the dearth of knowledge surrounding the experiences of underrepresented populations in the hiring process in computing, I sought to address this gap, and to consider the assets leveraged to overcome obstacles and successfully obtain a job. To ensure diverse representation and understanding of the phenomena, I recruited equal numbers of men and women that identified as Black/African American, Hispanic/Latina, Asian, or mixed race/ethnicity. Intersectionality also shaped the questions asked, and influenced the addition of prompts about the diversity at companies (e.g., Did you notice that the staff and/or interviewers were female? Black or African American? Etc.) and students' perceptions of inclusivity in the field (see complete list of questions in the Appendix). Intersectionality was considered during the interpretation of the results (represented as an outcome space) as well, for unpacking students' pathways to a career, and the challenges and discrimination they encountered (see Section 6.8).

6.4.3 Community Cultural Wealth (CCW)

As mentioned previously (in Section 2.3 of Chapter 2), CCW was defined by Yosso [Yosso, 2005], to describe six different types of capital that exist for people of color to overcome obstacles: Resistant, Familial, Aspirational, Social, Navigational, and Linguistic. In this chapter, CCW was used to describe how different populations may leverage these forms of capital to persist in computing and to attain a job. It should be noted that, for the purposes of this study, the definition for "Linguistic capital" was extended to include not only the benefits of speaking two or more languages, but also to consider students that used their communication to understand expectations and to talk through solutions to arrive at an answer during the interview process.

CCW was applied in this chapter during the planning and design, data collection (in terms of the interview protocol, see the Appendix), and in the interpretation of the results. CCW shaped C6RQ1, and the choice of participants, since I wanted to take an anti-deficit approach to understanding the experiences of students of color. When defining the prompts for semi-structured interviews, CCW was considered to create questions which may elicit understanding of the role of specific components, such as family, and their contribution to students' pathways to computing. Furthermore, during the interpretation of the results that emerged within the outcome space, understanding of students' conceptions of hiring was also better defined in the context of the established framework of CCW (see Section 6.8).

6.4.4 Theoretical Frameworks in Phenomenography

Although scholars undertaking phenomenography may utilize theoretical frameworks to answer research questions about a phenomena or students' experiences, they do not always make their application explicit. Furthermore, given the inductive nature of coding in phenomenography, they are not able to be applied during analysis itself. As such, when theoretical frameworks are employed, it is typically during the planning or interpretation (where the results are linked back to the overarching framework) phases. In Table 6.2, I summarize several prior works in computing and engineering that employed phenomenography. I include information about the phenomenon they investigated, which framework(s) they used, and where they mention applying these frameworks within the process. While these are not the only researchers in these fields who have utilized phenomenography, it should be mentioned that frequently frameworks are not discussed, or it may not be explicit how or where they are applied. However, for this work I describe in great detail the frameworks used and in what capacity.

6.5 Methods

This section describes the methods employed in this study. In each subsection, general information about recommendations/guidelines for the methodology, phenomenography, are presented, and then the information and decisions applied to this inquiry are described.

6.5.1 Participants

6.5.1.1 Overview on Participants in Phenomenography

Researchers disagree on a prescriptive sample size for phenomenography [Yates et al., 2012]. While some scholars claim approximately 15-20 informants is sufficient to understand the phenomenon in question and to find variation [Trigwell, 2000, Larsson and Holmström, 2007, Swartling et al., 2007], phenomenographic studies have been conducted with as few as 6 participants [Peters et al., 2014]. Other researchers have noted that rather than trying to obtain a precise count, they focus on reaching saturation [Yates et al., 2012, Dringenberg et al., 2015]. Saturation is defined as the point where a researcher has sufficient data to establish an "in-depth understanding" [Creswell and Clark, 2017], and where no new conceptions emerge [Sandberg, 2000]. However, in phenomenographic studies, variation is considered key to reconciling informants' accounts and to developing a "nuanced picture of relevant experiences within a cohort" [Berglund, 2004, p. 73].

Author(s): Reference(s)	**Phenomenon of Interest**	**Framework Applied**	**Phase(s) Applied** (Details, Where Indicated)
Kinnunen & Simon: [Kinnunen and Simon, 2012b] [Kinnunen and Simon, 2012a] [Kinnunen and Simon, 2011]	What are instructors' perceptions of students' success?	Bandura's theory (1997) of self-efficacy	Interpretation (contextualizing results)
Dringenberg: [Dringenberg, 2015]	Engaging with ill-structured problems, which have been defined as having the characteristics of engineering work, including a lack of information given, ambiguity within the process, multiple possible solutions and flexible means of evaluating solutions	Adaptation of Jonassen's classification of problems	Interpretation (situate the phenomenon of interest within the wide range of problem solving literature)
Peters: [Peters, 2018, Peters, 2014]	How students experience participation in CS and IT	Lave and Wenger's social theory of learning and identity	Planning; Data collection (protocol development); Interpretation
Smith: [Smith, 2015]	The qualitatively different ways that African American undergraduate women in engineering experience faculty mentoring	Intersectionality	Planning (RQ development, methodology selection); Data collection (participant selection); Interpretation
Mendoza Garcia: [Mendoza Garcia, 2016]	Descriptive path for the ability to address complex socio-technical systems, ways problems seen and approached	Variation Theory	Planning (methodology selection); Interpretation
Salzman: [Saldaña, 2015]	Students' experiences with transition from pre-college engineering programs to first-year engineering	Self-Determination Theory	Interpretation (Yet author states work not initially guided by this theory, the results aligned with aspects of it)
Jordan et al.: [Jordan et al., 2019]	How Navajo engineers experience, understand, and apply engineering design and practice in the context of their culture and community	Culturally responsive perspectives; Border-crossing framework (by Aikenhead)	Planning (methodology selection); Data collection (participant selection and protocol development); Interpretation

Table 6.2: Summary of phenomenographic inquiries conducted in computing and engineering

Given the critical role participants' perceptions play in developing an understanding of the phenomenon, it is recommended that selection is done with careful consideration to the goal [Boustedt, 2008]. As such, variation and purposive sampling are considered central facets in phenomenography [Reed, 2006]. Purposive sampling refers to the non-random selection of participants based on the researchers' judgment, and prior knowledge of the subjects.

6.5.1.2 Participants in this Inquiry

The participants in this study consisted of 16 full-time undergraduate computing students, all of which had completed at least one technical interview and received at least one job offer. Participants were identified through a survey administered via Qualtrics which was conducted at three metropolitan universities in Florida. The survey administered included 46 questions in total, and asked self-reported demographics, questions about the students' academic standing (year in school, major, and GPA), and inquiries into the students' experiences, persistence, and interests. The experiences examined included professional (e.g., number of hours working in a computing job, number of technical interviews and job offers) and cultural (e.g., social support or caring for a family member) items. Given the goal of understanding how minoritized populations leverage their own inherent capital, and in alignment with the tenants of phenomenography, a diverse sample was sought, in terms of their self-reported gender, race, and ethnicity. The participant details are outlined in Table 6.3. Pseudonyms were chosen by the participants, and all students were in their 3rd year or higher.

Pseudonym	Major	Gender	Race and/or Ethnicity	# of Interviews	# of Job Offers	Home Support: Extremely (4) to Not at all (0)	Friends in Computing
Steve	IT	Male	Asian, White	1-2	1	3	More than 10
Deanna	IT	Female	Black or African American	1-2	3	2	1-2
Frank	CS	Male	Hispanic/Latinx	5-6	2	4	5-6
Maria	CS	Female	Hispanic/Latinx	9 or more	3	4	More than 10
Tulip	CS	Female	Asian	1-2	1	4	More than 10
Alessia	CS	Female	Asian	1-2	2	1	3-4
Eliza	CS	Female	Hispanic/Latinx, White	3-4	5 or more	2	5-6
Ravi	CS	Male	Asian	7-8	3	2	3-4
Michael	IT	Male	Black or African American, Asian, and Hispanic/Latinx	3-4	1	4	1-2
Alex	CS	Male	Hispanic/ Latinx	9 or more	3	2	More than 10
Kevin	CE	Male	Black or African American	5-6	2	3	5-6
Leia	CS	Female	Hispanic/Latinx	9 or more	1	4	More than 10
Ramon	CS	Male	Hispanic/Latinx	9 or more	2	4	3-4
Jordan Henry	CS	Male	Black or African American	9 or more	3	4	5-6
Julia	CS	Female	Black or African American	5-6	1	4	1-2
Taylor	IT	Female	Black or African American	3-4	3	4	3-4

Table 6.3: Participant information

6.5.2 Data Collection: Semi-Structured Interviews

6.5.2.1 Overview on Data Collection in Phenomenography

Data collection for phenomenographic investigation is often conducted with semi-structured interviews [Larsson and Holmström, 2007, Bowden et al., 2000, Trigwell, 2000, Akerlind, 2012], although open-ended questionnaires, think-aloud methods, or observation may also be employed [Han and Ellis, 2019]. The content/outline for interviews must be designed in advance, and typically includes open-ended questions to explore the phenomena. To probe deeper on particular subjects and to spur reflection, follow up questions are also common, which limits the usage of entirely fixed and structured protocols [Bucks and Oakes, 2011]. The conversation may also naturally veer off track, leading to the evolution of extemporaneous thoughts and topics [Boustedt, 2008]. It is also suggested that individuals can be encouraged to discuss their experiences in depth until both the interviewer and participant reach a mutual consensus on the phenomenon [Booth, 1997, Svensson, 1997].

Pilot interviews are also considered a form of practice which are vital to data collection for several reasons [Bowden et al., 2005b, Akerlind, 2012]. They afford researchers the opportunity to hone their technique, such as being transparent about the goal and mitigating judgement in reactions [Bowden et al., 2005b, Dringenberg et al., 2015]. Additionally, pilot studies can be important to confirming the structure of the protocol, and to ensuring that the questions achieve commentary aligned with the intended topic [Bowden et al., 2005b].

6.5.2.2 Data Collection in this Inquiry

In this inquiry, semi-structured interviews were conducted with the 16 participants, which ranged in length from 21 minutes to 92 minutes. Three pilot interviews were also conducted, to test the interview protocol and to refine the interviewer's technique [Bowden et al., 2005a]. However, the data collected were discarded and not used for the subsequent analysis.

The semi-structured interview protocol was developed using the CCW, computing identity, and intsersectionality frameworks to focus the content. Ultimately, the goal was to elicit in-depth expressions related to each of the participant's attitudes towards and experience of the hiring process in computing, and their personal pathways and supports. There were roughly eight parts to each interview, the student's 1) opening statements; 2) backgrounds and definitions; 3) pathways into computing and particular jobs; 4) social support; 5) preparation for the hiring process; 6) their experiences with individual interviews; 7) perceptions of inclusivity in computing; and 8) closing. There were several open-ended questions in each part which served as a malleable framework, along with follow up questions, to probe deeper about their experiences and understanding their thoughts and reactions to each topic. The complete phenomenographic protocol is presented in the Appendix.

6.5.3 Data Analysis

6.5.3.1 Overview on Data Analysis in Phenomenography

Bowden has argued analysis should wait until all interviews have been conducted [Bowden et al., 2005b]. This serves to avoid introduction of new content, and potential overt and subconscious alterations to the protocol that may otherwise bias the responses. When interviews are used for data collection, they are also recorded for accuracy, and then transcribed verbatim for the analysis [Åkerlind, 2005, Tashakkori et al., 2020].

Reading of the transcripts occurs over multiple rounds, beginning with an initial pass to gain familiarity, and then additional rounds to extrapolate meaning, identify categories, refine them, and then to construct relationships among them [Kinnunen and Simon, 2012b]. The goal in phenomenographic data analysis is to develop an outcome space. An *outcome space* is considered the visual representation of a hierarchical set of qualitatively distinct, but logically related, categories [Akerlind, 2012].

Outcome spaces are used to solve problems and answer research questions, which can be applied to identify thresholds for meaningful experiences [Dringenberg, 2015], and to create distinct categories of the perceptions of these experiences [Booth, 1997, Åkerlind, 2005, Kinnunen and Simon, 2012b, Peters, 2018]. It should be noted that categories are meant to identify variations that arise from conceptions within a particular group of informants, rather than the conceptions of a particular individual [Akerlind, 2012]. Typically the logical relations in the structure of the outcome space are defined hierarchically, linearly, or as branching [Akerlind, 2012].

While there are not constraints on the amount of categories that should exist, Marton's assumption that there are a limited amount of qualitatively different ways that phenomena are experienced and understood has been described as implying there should only be a "few" [Marton, 1986]. Although "few" is open to interpretation, Cummings points out that more recent developments of outcome spaces typically remain limited to seven unique categories or less [Cummings, 2015]. However, researchers may also organize a smaller number of thematic headings, and then choose to represent the categories of description as sub-themes, which may result in larger overall amounts [Felix, 2009].

It should be mentioned that since theoretical frameworks were used to inform the questions asked, it is impossible to completely perform the analysis without any impact from them. Yet, including independent evaluators who are unfamiliar with the frameworks applied can help to mitigate their influence on the categories identified. Bowden recommends that multiple researchers review the transcripts to ensure consideration of additional perspectives and to strengthen the quality of the analysis [Bowden et al., 2005b]. There are two separate ways for doing so, via a coder reliability check or dialogic reliability check [Åkerlind, 2005]. Coder reliability check is described as "two researchers independently code all or a sample of interview transcripts and compare categorizations" [Åkerlind, 2005, p. 331]. As an alternative, dialogic reliability check, entails finding an "agreement between researchers is reached through discussion and mutual critique of the data and of each researcher's interpretive hypotheses" [Åkerlind, 2005, p. 331]. However, Åkerlind argues it may not always be feasible for multiple researchers to perform the analysis (e.g., in the case of doctoral dissertations), and notes that "high-quality phenomenographic research can be accomplished as an individual researcher working on one's own, though this does not preclude the possibility that group research work may produce a better outcome" [Akerlind, 2012, p. 121]. In the case of a single researcher conducting the analysis, Walsh suggests that it is important for the researcher to state their own positionality, and to perform critical self-reflection to describe theoretical leanings, assumptions, and relationships to the field under investigation to ensure trustworthiness and make potential biases and preconceptions more transparent [Walsh, 2000].

6.5.3.2 Data Analysis in this Inquiry

The tenants of phenomenography guided the analytical procedures for understanding the different ways of experiencing technical interviews and the hiring process in computing. Analyses were conducted only after all interviews had been completed

[Bowden et al., 2005b]. All audio from the recorded conversations were transcribed verbatim to establish written transcripts [Bowden, 2000]. Rather than using predetermined codes or guidelines, categorization in phenomenography is meant to emerge from the data itself. As such, the theoretical frameworks were not directly applied in the development of the outcome space.

A more complete look at the analytic process employed is depicted in Figure 6.3. Reading the transcripts to identify quotes, and recognizing the initial themes occurred over several rounds of iterations using Mendeley (see example in Figure 7.1 of the Appendix). The main researcher (the author of this dissertation) initially performed these steps alone. However, after initial themes were created and revised, a second researcher (another Ph.D. student), was given a "rich transcript" that contained a range of the themes and pertinent quotes already observed to separately highlight meaningful passages and to label themes. This researcher was unaware of the theoretical frameworks applied so that the themes established were not dependent upon them. The resultant transcript and list of themes identified was compared to the first author's list to refine the themes further. As mentioned, in this inquiry, decontextualized quotes were used to establish a "pool of meanings" [Marton, 1986]. Trello boards were used to aggregate the excerpts, with quotes assigned to a separate board for each C6RQ (see examples in Figures 7.2 and 7.3 of the Appendix).

After copies were made of the Trello boards, the main researcher and a third researcher (yet another Ph.D. student) independently arranged the quotes into separate columns, which contained headings pertaining to "themes." It should be noted that this third researcher was also unfamiliar with the theoretical frameworks applied, to mitigate their influence on the analysis. Upon completion, the two researchers worked to negotiate on the organization, and the themes were revised and finalized. The categories of description emerged out of these themes. After further

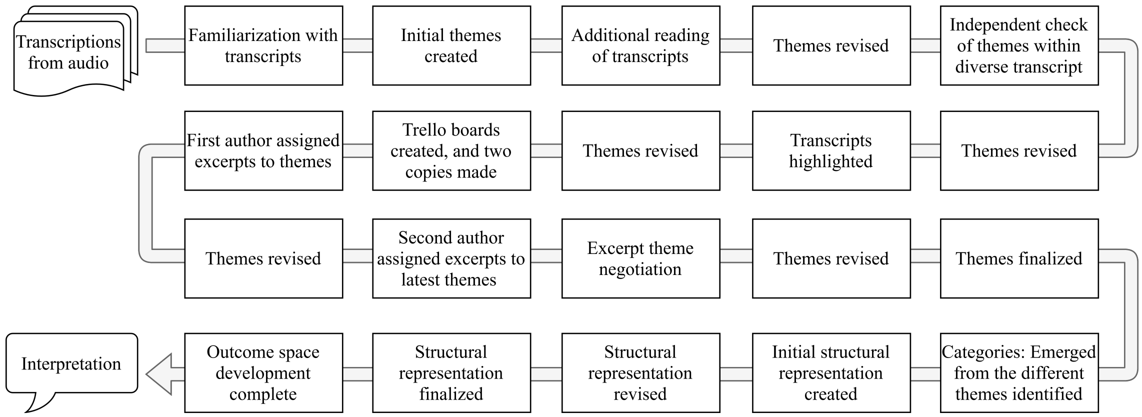

Figure 6.3: Process of phenomenographic analysis

iterations, the structural representation and visual depiction of these categories, the outcome space, was finalized.

6.6 Positionality

Phenomenography is an exploratory qualitative approach that necessitates interpretation as the outcome space is discovered. However, there is always a potential bias which can influence the design and analysis process. While it may be impossible to eliminate bias completely, the goal is to add transparency to the process and interpretation. I conducted all interviews and led the analysis efforts for each of the participants. Accordingly, my position and experience of the phenomenon under investigation should be made clear.

Being critical in reflecting on my positionality, I explicitly acknowledge the elements that influence my interpretation of the research findings: my race, gender, experiences in computing, are all elements of my position as the researcher or instrument of data collection. As a White, non-Hispanic, female student in computer science, I have experienced sexism, but have not had to contend with racism directed at me. I have undergone technical interviews and have previously worked in industry (although in another field).

Throughout the study, I leveraged my familiarity with the study's focus (i.e., preparing for technical interviews and having applied to and received job offers for computing roles) to develop interview questions which might delve into unique perspectives. I also used my prior experiences to form a rapport with the participants during the interviews. To establish rigor in the process and to build a rationale for decisions made, the larger community was called upon for assistance throughout the process. To ensure the interview protocol was congruent with the theoretical framings of this work, I consulted with an expert in qualitative research (i.e., my advisor). Additionally, an expert in phenomenography was consulted when planning the analysis (i.e., a researcher who has previously published on phenomenography), and when conducting the analysis (i.e., two other Ph.D. students as described previously in Section 6.5.3.2, and my advisor).

6.7 Results

This study sought to address two research questions: 1) How do students leverage the cultural capital associated with their self-identified racial, ethnic, and/or gender identity to obtain a job in computing?; and 2) What do the students feel would help to improve hiring in computing? In alignment with trying to understand perceptions of the phenomena under investigation, I first describe the themes identified in the data, and then I present the categories of description that emerged. To answer C6RQ1, I detail the support mechanisms students leaned on in their pathways to a career. Then, to answer C6RQ2, I present the recommendations on what could help to improve students' preparation for technical interviews, their education, and their experiences with the hiring process in computing.

6.7.1 C6RQ1: Themes Surrounding Capital Leveraged for Job Attainment

From the pool of meanings, 13 discrete themes emerged surrounding the capital students leverage to attain a job in computing: Pertinacity, Motivation, Gratitude, Confidence, Belongingness, Communication, Mentors, Peers, Faculty/Academic Advisors, Family, Personal Practice, Clubs/Groups, and University (Career Services and Coursework). Given the importance of considering the composite of related ways phenomena are experienced in phenomenography, the presence of each theme was established using a minimum cutoff. This value, which was considered to sufficiently represent a finding across perceptions, was five or more quotes centered on similar items. Below, each theme is discussed in greater detail:

6.7.1.1 Pertinacity

Several participants described encountering obstacles, and their own courage and conviction to persist and take it as a positive learning experience. Rather than feeling deterred by negative experiences or setbacks, they continued applying and going through the interview process. As described by Alex (a Hispanic male):

> I'm pretty sure I completely tanked it, but at least the way that I took it was it's a learning experience, now you have at least some reference point to know what technical interviews are going to be like and use it and learn and try to improve on it.

This theme also referred to the ways they dealt with discrimination, and the supports they leaned on to cope. Deanna (a Black female) described how she relied on National Society of Black Engineers (NSBE):

> You just have to just do your best and ensure that their biases and their mentalities didn't really affect my grade per se. I don't...I think thankfully I didn't have anything too detrimental, and I also just spoke to like my community, for example, NSBE. NSBE is my rock for sure in school. So a lot of my NSBE members, they went through what I went through, and they gave insight on how to just go about things so that helped a lot.

6.7.1.2 Motivation

Another theme that emerged were the factors that drew them to computing or made them apply for a particular position or company. While many students noted that at first they were desperate to just gain experience, the more confident they were in their own capability, and the more developed their computing identity, the more they began to look for other considerations like finding the work mentally stimulating. In addition, many students reported they were concerned with the "vibe" they got from the company, and that the company's values aligned with their own. Taylor (a Black female) noted: "I look for a location, the salary, and the company's awareness, like how they are with their people and their staff to make sure they don't treat people differently or wrong or anything."

6.7.1.3 Gratitude

Many students expressed feeling thankful to companies for working well with their school, or that made the interview process or that attempted to ease discomfort in the workplace through training, mentors, or celebrations of diversity. Particularly when students felt concerned that they had not seen certain material before, training served as a vital tool to encourage them. Steve (an Asian and White male) noted:

> They were actually good about education, they covered a couple of online courses for everybody to get more familiar with SQL and C#, which is what their main workflow is through. And, overall, it's actually been a pretty great experience.

Several of the females also mentioned how mentors within a company made the transition from academia to industry easier, and that same gender and/or race mentors served to provide inspirational role models. As discussed by Julia (a Black female),"The internship, it was really good. We did have a few weeks of orientation, and I always had a mentor by my side in case I needed help."

6.7.1.4 Confidence

Students from all backgrounds frequently mentioned suffering from imposter syndrome during the interview process. As defined by Rosenstein et al. [Rosenstein et al., 2020, p. 30], *imposter phenomenon*:

> is the experience of intellectual phoniness as perceived by high achieving individuals. These individuals have a great fear that others might discover that they are not as competent as they appear, attributing their successes to luck, knowing the right people, being in the right place at the right time, or even their personal charm.

Although many of the students struggled with feelings of inadequacy, they did report that obtaining a job helped to bolster their belief in themselves, and to solidify their computing identity. For example, Ravi (an Asian male) stated: "I thought I would be pretty nervous about it, but I was confident. After I got that first interview...or after I got the first job I just mentioned, I felt a lot more confident in myself and interviewing."

Interestingly, although all of the students interviewed did attain a job, they often felt they were average, compared to their high-performing and intellectually impressive peers. Such feelings are fairly common in computer science, as previous research has suggested that a high proportion of undergraduates in computer science struggle with imposter syndrome [Rosenstein et al., 2020]. Interestingly, women (at 71%) are more likely to feel it than men (52%).

In this work, confidence and speaking of one's own skill tended to emerge more often in the male participants as well. In general, males were more likely to discuss feeling capable, or being proud of what they have done or their abilities. Steve (an Asian and White male) commented:

> I really enjoy being seen as somebody who's responsible and does good work. Which they have very much told me that I'm responsible and do good work. Which is great to hear from an employer, even if it's a smaller company, and your boss is one sixth of the team. It's still great to have that relationship there where you are acknowledged for your work. I think that is kind of one of the driving forces. It makes me proud. It's not just show up there, collect the paycheck, don't get recognized for anything and go home. It's definitely, involved with, and even at the time of schooling involved with, what I was, doing and stuff like that. That involvement was pretty important.

6.7.1.5 Belongingness

Many participants did comment they think companies are trying for more diversity, and that they think in part, it may be the choice of the groups absent not to participate in computing. However, many students also commented that seeing others like them, or speaking to them, made them feel more comfortable, such as Maria (a Hispanic female):

> I think when I heard a girl on the phone that was, okay, cool. I was like, next. I think I got a little bit more comfortable. I mean, yeah, it made me feel good about it I guess. I knew the company was diverse going in. So I guess it was cool to see that confirmed. It's not just White Americans.

Likewise, Deanna (a Black female) commented:

> It definitely made it easier to approach the recruiters. I know for me, I feel more comfortable when I'm speaking to either a person of color and/or someone who is female, so that made it easier to approach the company.

It also served to encourage students, as mentioned by Taylor (a Black female) "It just made me feel that I know the company is diverse and they won't discriminate against you no matter what color you are. So it felt pretty good to see that diversity."

6.7.1.6 Mentors

Student often described how mentors or role models provided support during they process, either learning from them about what to expect in the hiring process or how to prepare, gaining coding practice, or leaning on them emotionally. Alex (a Hispanic male) described a mentor he was paired with through the Society of Hispanic Professional Engineers (SHPE):

> The main way that I learned about technical interviews and interviews in general and kind of the internships and all that stuff was my freshmen year I joined SHPE through the mentorship program. So through that, I was paired with a mentor who was of a higher class standing. I think he was the one that definitely pushed me to apply to internships and introduced me to it, and through that, as I made more connections in SHPE, everyone was just driven to have internships every summer or get as many opportunities as you can. So I would say that was how I got introduced to the interviewing, technical interview preparation, all that stuff.

6.7.1.7 Communication

While not all participants found being multilingual or bilingual to directly impact their technical interview, several mentioned the connection formed because of shared culture expressed through communication. Ramon (a Hispanic male) commented that "It helped if the interviewer was also a Latin person, I think it helped because it created that special connection between Latinos." In addition, the participants described how communication served as a valuable skill during hiring. They mentioned that companies often wanted candidates who were able to speak through solutions in technical interviews, and that it was also important to communicate with clients or other co-workers. Michael (an Asian, Black, and Hispanic male) stated:

> Soft skills to me means just being able to interact with the person and employer, being able to talk to them, look them in the eye, have a pretty

> understandable discussion about the topic. And I know, at least for me, definitely in the past, definitely in the past and a lot of people I know, they kind of just want to code and not talk to anybody, not have any interaction and that's just not the way the world works. So, definitely developing the skills to create strong relationships with other people is what I consider soft skills.

6.7.1.8 Peers

Often students mentioned the value of friendships, classmates, and peers that helped them to face adversity, to overcome obstacles, or to prepare. Whereas family was more likely to provide emotional support since they did not understand the technical aspects of computing or the hiring process, their peers were frequently mentioned as playing a critical role in persistence, understanding, and directly in learning about resources or what to anticipate. Maria (a Hispanic female) stated:

> As I got older, other friendships I've made have been in CS and it's definitely influenced me to keep going, I guess. Because I know there's more people doing the same thing as me, has the same interests. So its nice to have that.

In terms of technical interviews, Ravi (an Asian male) said:

> Right now, since everyone's looking for a job right now, we're juniors and seniors- interviewing is something that we talk about all the time. How... we compare tips and tricks to help each other out and stuff like that. So that's a really big topic that we talk about all the time. And what kind of resources we can use. I know you probably know Leetcode

> and all that stuff that people use, so we just talk about that. We split subscriptions and everything like that.

6.7.1.9 Faculty/Academic Advisors

Faculty members or academic advisors that provide counseling, emotional support, or guidance to students also were mentioned as preparing students for interviews or guiding them during the process. Michael (an Asian, Black, and Hispanic male) noted:

> I met with Mr. [name], who was IT advisor at [university name]. And he really helped me out with my resume. He helped me out with my interviewing skills, soft skills, things like that. And I definitely think that helped me to get a job, too.

Students also noted they may have a predilection for same race professors to learn about the process or particular companies, such as Deanna (a Black female) who said "I mainly reached out to professors and faculty that had ties to NSBE the organization."

6.7.1.10 Family

Students often reported their families did not understand the technical components of computing, so usually their family served to provide emotional support throughout the process. Frank (a Hispanic male) said:

> I would tell my mom say... about how the interview would go, more so at a, social, not really a technical level, but my interactions with the employees and things like that of the company. But I would never really discuss technical side since she wouldn't really understand.

However, several students did have family members that worked in the discipline, and they were able to contribute more though in terms of how to prepare, or even in networking to help obtain an interview. Maria (a Hispanic female) had a brother in the field said “My brother told me how to prepare for them, gave me some tips. He’s the one that told me to buy the book I mentioned.”

6.7.1.11 Personal Practice

Students mentioned that often knowledge in computing was developed beyond coursework, and instead they prepared for interviews in hackathons, side projects, and their own studying and preparation. Students also reported they often learned better by getting hands-on experience, as mentioned by Alessia (an Asian female) “I’ve always been more of a hands-on learner than any other type of learning. So the more practice I get in anything, the better I tend to understand it.” Michael (an Asian, Black, and Hispanic male) also described this as:

> Honestly, the personal projects was where I learned the most. I learned more from my personal projects than I did my whole four-year degree. So, if I were to tell anyone to do anything, it would definitely be start working on personal projects. I think those will take you way further than anything you could do in terms of interview preparation. Because you have these projects that you’re passionate about, that you’re knowledgeable about, and things that you can talk about in an interview, it’ll definitely portray a really good idea of who you would be as an employee, as a software engineer, or whatever it is that the person might be interviewing for.

6.7.1.12 Clubs/Groups

Students also mentioned that their membership in clubs or organizations (, e.g., NSBE, SHPE, or Upsilon Pi Epsilon (UPE)- the computing and information discipline honor society) helped them to build a community, and to learn about the process of technical interviews. Leia (a Hispanic female) commented:

> I guess it all began with UPE. I feel like if I had never been a member of UPE, or just been involved with UPE, I would have never known what to do in terms of technical interviews. Yeah, definitely, because as I said, just by being a member of UPE and in the Discord, you get so many resources and people that talk about the interview or someone will say, "Oh, I got a coding challenge from a company." Then someone will say, "Oh, yeah, I did that. It was hard. It was easy. I don't know. The Leetcode easy to prepare." Just... UPE opened so many doors for me to let me know what it was like and start getting ready for interviews.

Another student, Eliza (a Hispanic and White female) said:

> I've been involved with SHPE and I feel like that's one of the biggest things that has helped me since my freshman year. They've helped me with professional development, technical stuff, just being prepared for conferences, interviews, really a lot of good stuff.

6.7.1.13 University (Career services and Coursework)

Students often commented that coursework served more to develop fundamental knowledge than to help with the technical interviews themselves. Courses such as programming, algorithms, and data structures though were often mentioned as instrumental as building a base for further preparation. Alex (a Hispanic male) said "I definitely think that data structures and algorithms has helped me a lot in preparation and just in technical interviews in general."

6.7.2 C6RQ1: Categories of Description, Support Mechanisms

Extracts from the semi-structured interviews were used to delimit the categories of description, and to communicate the differing support mechanisms students may leverage to succeed in their pathways in computing. As shown in Table 6.4, five main categories of description were identified from the analysis: Intrinsic Characteristics, Capitalizing on Experience, Community, Preparation, and Organizational. Each category is described further, along with a definition of the broader label.

Category	Description
Intrinsic Characteristics	Refers to the personality traits a student may leverage in the face of obstacles
Capitalizing on Experience	References a student's use of past experience or familiarity with a question, topic, the hiring process to succeed in future encounters
Community	Refers to leaning on social supports, whether individuals or groups, when seeking opportunities, preparing for technical interviews, learning about the hiring process, building connections, and/or facing adversity or setbacks
Preparation	Considers the pathways to learning about computing topics, and what to expect from the hiring process in computing and industry
Organizational	The larger groups and institutions that students relied on to develop a foundation in computing, to learn about the interview process, to develop resilience, and to discover opportunities

Table 6.4: Categories of description for student support mechanisms in C6RQ1

6.7.3 C6RQ1: Outcome Space

Figure 6.4 illustrates the outcome space for C6RQ1. It displays the relationships between the categories of description (the support mechanisms), as well as a visualization of the contribution for each of the themes previously detailed. These themes, and the way they connect to the support mechanisms is described in terms of a hierarchy pertaining to an individual's locus of control over extrinsic influences, from least control to most control.

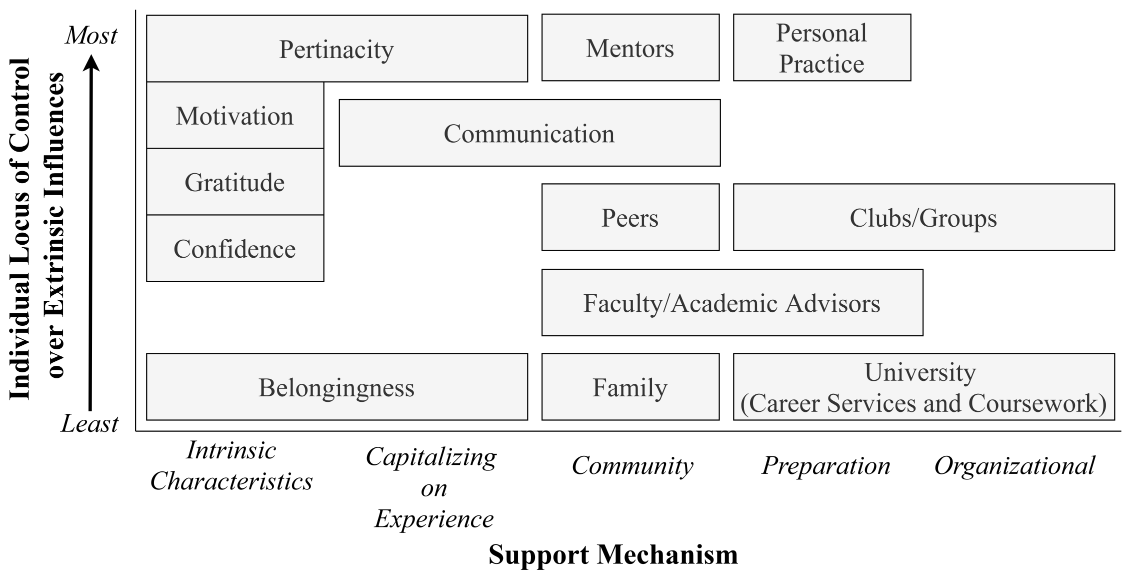

Figure 6.4: Outcome space for C6RQ1

Locus of control is a concept first described by Rotter (1954), that refers to the extent that individuals believe they can control the situations and experiences that impact them [Rotter, 1954]. Aspects that play a role in students' support mechanisms were considered as shown. For example, while family may not be something that a student can choose, they do have a high level of control over who they consider or rely on as a mentor. Likewise, they may be unable to control the content taught at their university directly, but they can choose to participate in a club or group (although again, still limited in what this club or group may cover). Students can also affect their own personal practice in terms of the way they develop knowledge and their own strategy towards answering questions in interviews. Even for intrinsic characteristics, while there are many items a student can control, such as their own pertinacity, motivation, gratitude, and confidence, their belongingess in computing or at a company is often shaped by the way others treat them, the diversity observed, and the level of inclusion they see and perceive.

6.7.4 C6RQ2: Themes Surrounding Recommendations to Improve Student Preparation and Hiring

From the responses within the pool of meanings, 11 themes emerged surrounding potential ways to improve student preparation and the hiring process in computing. Each of these themes fell along the axis of three agents for change — Industry, Academia, and Students. The complete list of themes for each is:

- *Industry*: Clarity of Expectations, Candidate Communication, Interviewer Disposition, Welcoming Atmosphere, Revise Interviews
- *Academia*: Tech Specific Career Support, Practical Example, Course Creation
- *Students*: Managing Expectations, Apply Past Experiences, Preparation

6.7.4.1 Industry: Clarity of Expectations

Students often mentioned a disconnect between what they expected and what they encountered in the interviews. Deanna (a Black female) said "I would say I wish they gave kind of a little bit more clarification just because the interview I had in the interview I was expecting were completely different."

They mentioned that industry could improve by giving more information and resources upfront to know what to expect, and to prepare. As Tulip (an Asian female) commented "with the first few that didn't give me resources. With the next ones I have that are giving me resources, it makes me feel a lot more confident and prepared and that's probably the only thing."

6.7.4.2 Industry: Candidate Communication

Many participants commented they wanted more communication from companies, and prompt and timely responses about their status. They stated there was a lengthy period between when they applied, and when they heard about receiving an interview, as described by Leia (a Hispanic female):

> When I first started applying, I started applying back in August, and I didn't hear back for a while from some companies. Now that I'm already ready to sign an offer, I'm hearing back from companies and I'm like, well, but I applied two months ago. I don't want to interview now, and I already have an offer. I know they get a million applications, too. Some companies just get too many applications, but maybe they can just reply faster to applicants and let them know the decision maybe. Not like two months after.

Given that students may have heard back from other companies in the interim, and often had to make rapid acceptance decisions, they mentioned it would help to know their application was received, and/or if they were still contenders. Likewise, participants stated that frequently they never got a formal rejection, which added further frustration. Ravi (an Asian male) commented that "I don't even think I got any feedback at all. I don't think I got a 'Oh sorry, we didn't want you.' Or anything like that. I just never heard back."

Contrarily, students felt there was huge merit to providing updates, and cited the benefits when they did hear back, such as Frank (a Hispanic male):

> They were very communicative, as I said completely amazing experience, because even though they didn't really need to send a follow up email like explaining why, they just mentioned 'We still think you're a little bit young, but we really loved what we saw, there was only good things said about you from our people.' It was very encouraging. So that really helps in general, even though it was not an offer. You don't consider that a failure because it really builds you in a way. It really helps you to still feel confident about your capabilities.

6.7.4.3 Industry: Interviewer Disposition

The way that the interviewer and recruiter acted often played a big role in students' impression of the interview and company. Not only could it deter them from proceeding with accepting an offer, but it could also impact performance on technical components as described by Maria (a Hispanic female):

> I'm wondering when they don't seem that friendly. It's definitely very discouraging during the interview to ... I don't know, that constantly deter off my confidence and stuff, so that's not good. They shouldn't be acting like that. And it's probably not me. It's just, I don't know.

Even within the interviews at the same company, students reported there was often a "good cop/bad cop" dynamic, and that they were more likely to be successful when they felt the interviewer was attentive and positive. Michael (an Asian, Black, and Hispanic male) described his experience interviewing at a large technology company:

> So, the technical interviews, there's two of them. So, it was kind of I feel like a mix of reasons on why the first interview was kind of rough, primarily because I just completely froze and I was nervous. It was my first big boy interview. But I can tell that the interviewer was kind of annoyed with me because I was struggling and I could hear him on his phone texting. And I would ask him a question and he would just be like, "Ah." So, that kind of sucked. The second interviewer though was very responsive, very attentive. And I did perform better. Unfortunately, I didn't get the job. But that's beside the point. But yeah, so the first interview was kind of rough, just from both ends, me and the interviewer. But the second one was a lot friendlier.

He continued on to say:

> The second interviewer, I can't say the same for him. He was way more responsive, walking me through the problem when I had questions. And I think having someone there who it doesn't feel like they've already given up on you, I think that definitely affects performance.

6.7.4.4 Industry: Welcoming Atmosphere

Creating a welcoming atmosphere was important to students not only during the hiring process, but also in the workplace. Many students reported that their interviewers were White or Asian males. Although students did occasionally see women, Hispanics/Latinxs or Blacks/African Americans, they were more likely to be recruiters, particularly at career fairs centered at targeting diverse populations (e.g., those hosted by SHPE), than to serve in technical roles. Julia (a Black female) commented "I guess one thing that kind of bothered me a little bit is the fact that

I haven't had an interview yet with another woman who's in my field. All of them have been guys."

Several of the females also noted being the only one in their department, and that they may have been talked down to, or given different tasks than their peers. While they did not often directly label the sexism or racism they encountered, they also did not always feel that the field was inclusive. Many were uncertain what could be done to improve the situation, however, students such as Deanna (a Black female) suggested companies take the time to ask:

> I think it would, what's one thing that could be really insightful is just...the very few that are in computing that are from diverse groups, I think if communication was with them a lot, if there was more communication with them in terms of, like what you're doing right now, asking me "what do you think could help with increasing the diversity in computing?" I think companies or any of the disciplines can do the same thing. They could just reach out to their employees that are from these diverse communities and ask them, ask them the question that you're asking and ask them to help with increasing the amount of people in, and also like giving their support towards it. I think. And I also think the responsibility of bringing in more diverse individuals shouldn't fall on individuals that are already diverse. It should be a concern for everyone in the company. I don't think Black people should just bring in Black people. I don't think women should just bring in women. I think it should be a concern for every discipline...for every person there. So if you don't identify with either of those groups, it should still be your concern and it should still be something you're striving to do.

In terms of making the field more inclusive, students also mentioned how important support could be. As Leia (a Hispanic female) suggested:

> Maybe we can help more women succeed and we can have more African Americans and just more Latinx succeed in computer science by offering more support and whatever else they might need. Especially since there are kids in high school or middle school, they can start learning what computing is like and they might go into it later in the future if they started growing that passion for computing since they were little.

6.7.4.5 Industry: Revise Interviews

Overwhelmingly, students noted that the hiring process in computing was not always a great reflection of their skills or performance. They often preferred more of a focus on behavioral assessments, particularly when interviews felt like organic conversations, or even take-home assignments. They spoke about how when coding in technical interviews, such settings were unrealistic, because even on the job they could always search online for solutions when they got stuck. As Alex (a Hispanic male) commented:

> I'd say that the main thing that I wish was a little different is that they maybe moved away from those type of questions where it's like write me a function that does this, or write me code, write me code, because a lot of the times when you're going through a problem, whether it be in the workforce or just in general, you have a lot of resources that are available. In my experience, when I've been on internships, my managers have never had a problem with me looking up something or using code that I found online. Obviously they don't want me copying and pasting

> the whole thing, but that's something that I guess I have kind of seen a tradition.

In addition, they spoke to the immense preparation required, as with Jordan Henry (a Black male) who said "I wish there was no coding challenges. I understand that it's a very vital aspect, but at the same time it feels like there's a need for preparation beforehand. And it doesn't really showcase your actual skills."

6.7.4.6 Academia: Tech Specific Career Support

While many students mentioned their campus did have a career services, they also expressed they would prefer more technology-specific career support. They mentioned that many times the support and awareness of what to expect comes from organizations and clubs on campus, so even raising awareness of those opportunities for students early in their careers could be beneficial. In addition, they requested mock interviews or practice with speaking to develop communication skills, and also requested that departments consider more hands-on and practical examples. Ramon (a Hispanic male) commented that theory was well covered, which was something several students expressed, but that:

> The actual practice, the hands-on, it was not covered that much. So to put an analogy, for example if someone who goes to a bootcamp is more prepared on that part that [university name] lacked of teaching. Because for example...It's a challenge, I understand the university. It is not there to do that. You know, the professor are not up to date with the latest technology. They doesn't work in the industry. So that is a gap there that the bigger university doesn't cover, that you have to learn about yourself. And when you go to the market, you'll see that it is like, Wow, there is a lot that I need to learn, that I didn't learn in the school.

6.7.4.7 Academia: Practical Examples

Students frequently mentioned they would like practical examples and more hands-on training in their coursework. They mentioned they found a lot of what was covered in class to be fairly simple relative to what they encountered later, and as such, would appreciate being challenged. Jordan Henry (a Black male) stated "I would say more practical usage of programming, like web development or, what is it? Mobile development, website development. Just more applications of programming rather than just the topics themselves."

In addition, Michael (an Asian, Black, and Hispanic male) noted:

> I think just making it way more hands-on and a little bit more updated I think would have been better. The coding classes, a lot of the coding classes I took, only a few of them really challenged you. A lot of them kind of, professors gave you pretty much the solutions and didn't really challenge you much.

6.7.4.8 Academia: Course Creation

Many students encouraged universities to create an elective or core class to help students prepare for the hiring process, and develop their hard and soft skills. Such a course could include practicing interviews, learning how to approach programming problems step by step, and solving questions as needed for technical interviews (e.g., quickly and on a whiteboard). They noted how they often had outside commitments that interfered with their ability to prepare more, such as caring for family members, or even studying for exams in classes. As described by Leia (a Hispanic female):

> I know school wouldn't do interview prep, like in terms of, I guess, coding questions, but maybe...Actually, that could be a class, problem solving,

> kind of. Cause I know, I think Programming III...It really depends also on the professor you take as well. I don't know. I'm not sure. I guess maybe problem solving, tips and tricks of how to do a problem, because sometimes, you might want to do extra work in terms of...But you might want to sit down and do Leetcode but you're already so tired from the work that you're doing for five classes that you're taking that you don't have the energy to sit down and do Leetcode. Maybe one of those classes could be just interview prep on problem solving.

Ravi (an Asian male) felt similarly:

> Mock interviews definitely, how to prepare, how to interview, how to apply basically, how to network, stuff like that. So all those... or quick meetings that they have after class, except go how to network or how to do technical interviews. If you put all those into one class, I think that could be super [inaudible 00:21:06] and students are required to take it. Because if you have these meetings and people don't have time or people have jobs, it's hard to do on top of classes, so if you had your own three, four credit class, that would be super beneficial definitely.

Other students mentioned how they felt uncomfortable speaking, or how they noticed others in the department struggled with communication. As such, they felt gaining practice could help to better prepare, as emphasized by Michael (an Asian, Black, and Hispanic male):

> I think providing students with some sort of soft skills interviewing course or something, that's definitely neglected in both or just the engineering department. I think giving students that knowledge and really pushing them out of their comfort zones would help everyone tremendously. Like

> I said, for a lot of those students are really headphones on coding away, which is great. There's a lot of smart kids in that degree. But it takes more than just being able to code to have a successful career. So, I think, man, even just giving speeches or something, being able to do public speaking more or a mock interview course, maybe you do like, what, five interviews in the semester or something, I think that would be a great experience.

At one point Stanford did offer such a course [Stanford, 2017], and students interviewed also pointed to a competitive programming class they had heard about from friends at another university which helped their students gain experience with questions similar to those encountered during technical interviews. However, such opportunities were absent in the schools examined, and are more likely to be the exception rather than the norm for students.

6.7.4.9 Students: Managing Expectations

Students frequently observed a lot of variability in what they encountered relative to what they had expected. They noted differences between larger and smaller companies, and cautioned students against going in with preconceived notions. As Steve (an Asian and White male) commented:

> I suppose to go in with a very open mind on what they can be, and what they may end up being. I mean, it could be anything from not having a tailored suit could cost you the job, or you go in wearing the same clothes that you've worn in high school and you will be completely fine. I mean there's just so much difference in what it could be, and what I've had friends experience versus what I've experienced. I mean it is a complete just. . . open. . . just an open book of what it could be.

Also, they suggested applying to as many jobs as possible since each was so distinct, and it could be a lengthy process to even get an interview. Ravi (an Asian male) stated that students should "Not to get super stoked about an interview or get your hopes up, or put all your eggs in one basket for one interview."

6.7.4.10 Students: Apply Past Experiences

Students also suggested it was important to apply past experience or knowledge to solve problems during the interviews. Frank (a Hispanic male) commented:

> So with the first [interviewer], as I mentioned, I was able to talk to him, and it would really just promote me going back in my head to any practice or anything that I had learned that would help me with this.

6.7.4.11 Students: Preparation

Students regularly commented on the importance of preparing for interviews in advance. Frank (a Hispanic male) noted:

> I think that in general, the preparation is an amazing tool that we have, and it could be definitely exploited better. To help issues as imposter syndrome be overcome, in a healthy way, rather than I guess. . . I'm sorry. I would just finish off by overcoming confidence issues in a healthy way.

Also, it was considered important to spend as much time as possible preparing, as indicated by Kevin (a Black male) who said, "You have to prepare sometimes months in advance and not just maybe a few days or weeks in advance."

Students mentioned doing mock interviews with friends, online resources, and preparatory books, such as those suggested by Julia (a Black female):

> I think with technical interviews, it's very important for you to check your resources. If you ever have free time, it's always best to try and do some practice problems with Leetcode, HackerRank. Or you can... there's this really good book for prepping called Cracking the Coding Interview. It's a really good book for programmers. Those are really what I'd encourage people to use if they're trying to prepare for a technical interview.

6.7.5 C6RQ2: Categories of Description, Obstacles Encountered

From the themes surrounding recommendations to improve student preparation and the hiring process in computing, five main categories of description emerged, as described in Table 6.5. Specifically, these categories correspond to the kinds of obstacles students encountered: Uncertainty, Interview Techniques, Time Demands of Preparation, Anxiety Management, and Improving Inclusivity. While each category referred to a pervasive concern cited by the students during the interviews, there was also variation in their perceptions of the experiences. For example, discrimination or a lack of inclusivity was viewed differently by those not identifying with a particular gender, race, or ethnicity, relative to those students which did. Given the different scope and goal of C6RQ1 and C6RQ2, the categories had a different relationship with the themes. For C6RQ2, the categories are described more completely below since the recommendations previously discussed by each theme (as solutions) correspond directly to the barriers noted, which is important to understanding the existing challenges.

Category	Description
Uncertainty	The ways the student felt unprepared, unsure of what to expect in the hiring process, or where they stood in relation to their performance on the interviews.
Interview Techniques	The need to acquire technical or behavioral skills in order to navigate through interviews.
Time Demands of Preparation	Concerns about the amount of time required to study for technical interviews. Also referred to commitments which limited students' availability for preparation such as family, friends, courses, health issues, or other jobs.
Anxiety Management	Factors that could impact performance in the interviews, and which were sources of stress during hiring.
Improving Inclusivity	Feelings of isolation, discrimination, and reduced diversity, and need for the hiring process, universities, and industry to be more inclusive.

Table 6.5: Categories of obstacles encountered with the current hiring process in computing for C6RQ2

6.7.5.1 Uncertainty

Students frequently described not knowing what to expect from the hiring process, since it could be so variable. As Deanna (a Black female) commented:

> I wish I had more insight, I would say for the technical portion, because the first interview I was spazzing about it because I wasn't sure what to expect. So I was like, 'Do I prep for another FizzBuzz challenge? Do I prep for a more complicated technical interview? Should I prep for whiteboarding?'

Students also reported that they may have been asked about content they were unfamiliar with since it had not yet been covered in their coursework. Many students cited their own inexperience as the biggest challenge in the hiring process. Jordan Henry (a Black male) commented, "I would say not knowing anything, honestly. I was still taking my second programming class and I just didn't know there was a lot more to programming other than the basics from what I've learned in the first class."

In addition, the participants expressed that their limited experience may impact their confidence. As Ravi (an Asian male) articulated:

> I think the biggest challenge for me was I just was at a position where I didn't know that much about the field of computer science. So it was hard for me to feel confident in what I was saying, or feel like I had the skills necessary to get the position.

6.7.5.2 Interview Techniques

The participants commented that the hiring process in computing was distinct from other fields. As Taylor (a Black female) said, "I don't think with other fields they do coding assessments or they ask you to troubleshoot things straight on the spot." Furthermore, they noted that significant preparation and skill acquisition were required to perform well. Students attributed this to multiple reasons, including that questions asked could span such a wide range of topics, and that they often required very specific knowledge to answer. As Kevin (a Black male) mentioned, "the questions weren't odd, but they were very specific. They were very conceptual in the sense that you had to know every single underlying detail, like a framework or a language you used."

Participants also mentioned that preparation usually required reviewing material that they had not seen or used for quite some time. Tulip (an Asian female) revealed:

> In the technical department, my biggest challenge was definitely trying to go back to the things that I had learned about maybe half a year, a year ago. The topics that they were asking me, they didn't give me anything to prepare. And it had been a while since I first learned it. And I don't generally use those things in my projects today.

In addition, they mentioned how often technical interviews were more reflective of having the capability to answer questions in a specific way, rather than demonstrating how someone may perform in the role. Michael (an Asian, Black, and Hispanic male) commented that "those problems don't necessarily carry over to your skill as a software engineer. It's a very niche skill set to be good at those problems."

6.7.5.3 Time Demands of Preparation

Students frequently mentioned that they had limited time to prepare for technical interviews, as a result of other commitments. As Ramon (Hispanic male) explained "I don't have a lot of free time because I have a family. I was also working full-time while going to [school name], and while doing interviews. So I didn't prepare that much."

6.7.5.4 Anxiety Management

Often participants reported that the stress they felt during the interviews, or as a result of interactions with the interviewers, hindered their performance. Leia expressed that "I was just really nervous about the interview, so I feel like I wasn't doing my best." Similarly, Julia (a Black female) stated:

> Lowering my anxiety was the biggest challenge, because again, I was intimidated the first time because I didn't really feel like I had enough interaction with real founders and recruiters to really...Yeah, that was really it. I was just really intimidated by them.

Even when students were well prepared, they reported feeling intimidated. Eliza explained that:

> I definitely feel like just the psychological factor of I'm applying for what sounds like a really technical position in the job description. That was just a psychological thing. I was stressing myself over it. Felt like I did myself a disservice by over-preparing, overstressing for it. I would have done. . . my nerves would have been better during the interview if I had just relaxed.

6.7.5.5 Improving Inclusivity

Many students commented on the lack of diversity they observed in their classes and in the workplace. While they wished things were different, they expressed it was unsurprising. As Alessia (an Asian female) mentioned, "I understand that the field of computing is mostly male dominated currently speaking, can't say I'm not used to it. Well, you can't really do much about it." Similarly, Deanna (a Black female) commented:

> I would say for this company, it was a little bit, there was definitely a lot less, people who looked like me, cause that's how...that's when I feel most confident, when there's someone who I can relate to in terms of whether it's a female recruiter or a Black recruiter or both. For this company, it was a lot, there's a lot less, there's fewer opportunities to do that, but I was kinda told that prior to applying to the position and on the research, what I've noticed over the years with that company. So I would say it, I just kind of prepped myself for that. Like I wasn't expecting a lot of diversity. There's more than I expected for sure, but I wasn't expecting that much.

Several students also spoke about the discrimination they faced, as shared by Tulip (an Asian female):

> I don't think anyone has outright said that I can't do something or they won't let me do something because I'm a female or because I'm a person of color. But I definitely think that there were instances of the way people have talked to me and the different tasks that I've been given based on the fact that I was a female person of color.

In addition, even if students did not directly report experiencing racism or sexism, they were aware of issues others faced. Steve (an Asian and White male) said:

> I still feel that there's like a stigma being a woman working in a tech industry. You may get harassed. You may get called things. You may have other people predisposed to kind of how women 'Women can't do whatever, why don't you just go Google something.' Something like that. Something almost, almost... like a parody of itself. Except that I know that it happens because I have friends that are women in the tech field, and these very Onion-esque article headline things happen to them in real life.

6.7.6 C6RQ2: Outcome Space

The outcome space for C6RQ2 is illustrated in Figure 6.5. As already mentioned, the categories of description surrounding the obstacles encountered are depicted in relation to the particular agent for change (academia, industry, or students). The relationship between the themes and the categories are also presented. For example, academia creating a course for students to help prepare them for technical interview would not only serve to help reduce anxiety by familiarizing them with the style of questioning they could later encounter, but it could also help with the time demands of preparation. Given that students may have different commitments, and may be caring for family or working other jobs (as described in [Lunn et al., 2021b] and by students in the interviews), offering a course within the curricula would ensure all students are aware of the expectations ahead, and could give them the opportunity to practice without the burden of trying to find additional time outside of that already allocated for coursework.

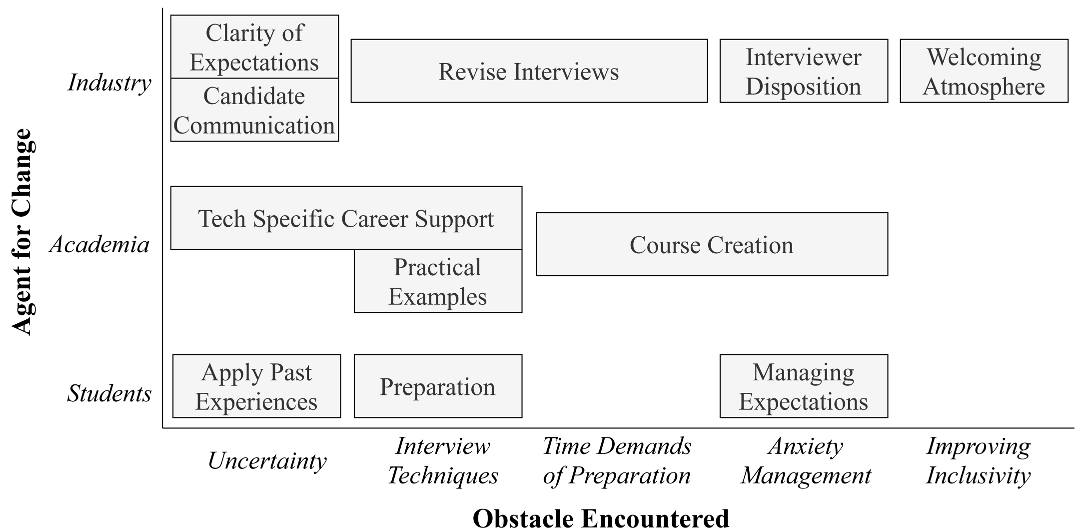

Figure 6.5: Outcome space for C6RQ2

6.8 Discussion

6.8.1 C6RQ1: Leveraging Capital to Attain a Computing Job

Students' intersectional backgrounds contributed to how they navigated social, educational, hiring, and workplace interactions. Intrinsic characteristics, including their pertinacity, motivation, gratitude, confidence, and belongingness spurred them on despite adverse interactions or negative encounters. While students reported facing many tough or challenging experiences in school or during hiring, the overall mindset and reactions to these encounters was one of optimism, and students used this aspirational capital to maintain a positive outlook and attain a job. This aligns with prior literature which also demonstrated that URMs may describe obstacles overcome as precedents to are used to achieve success [Garibay, 2016].

One of the themes previously mentioned by Garibay, in work on URM students in STEM, was gratitude and "appreciation for their parent's sacrifices and respect for the adversity that they had to undergo in order to give their children a better life" [Garibay, 2016, p. 71]. Likewise, students in the interviews expressed how much their families had done, how they felt lucky relative to others they knew, such as a student whose mentor was dealing with immigration issues. In the context of hiring and industry, they also expressed gratitude whenever they felt like a company celebrated diversity, or when they saw others that looked like them. While often the women in the study expressed they may be isolated in their department or building, those students who had the opposite experience found it encouraging, and inspirational. For example, Maria, a Hispanic female, discussed how "I feel like some of the senior women are Latina, which is just cool. We're definitely there, we're there." Although her experience was not typical among the women interviewed, it spoke to the potential benefits of companies that are more diverse, and particularly, where women of color may serve in higher level positions.

Consistent with the findings of other researchers [Mahmoudi, 2017], students reported that most frequently interviewers for the technical interviews were White or Asian males. If females were present at all in the hiring process, it was most likely the recruiter or human resources manager. Yet perceptions of inclusivity in the field and at a company were only occasionally cited as problematic. In general, this lack of diversity was often normalized as being expected.

More often than not, students noted that although they personally had not faced racism or sexism, they knew others that had (as described in section 6.7.5.5). Among the students that reported facing micro- or marco-aggressions, the way students spoke of such instances and encounters was noteworthy. Racism and/or sexism were spoken of with an air of resignation. Students frequently tried to ignore such experiences and coped with discrimination by leveraging social capital to lean on their community (as described by the theme of pertinacity in Section 6.7.1.1, in which Deanna mentions leaning on NSBE). Typically they relied on role models and/or peers. This further supports the work of others that have described how peer relationships and support can serve as types of navigational capital [Samuelson and Litzler, 2016, Denton and Borrego, 2021]. Furthermore, professional organizations often served as counterspaces for minoritized students to challenge their sense of marginalization, and to help them prepare for hiring (as described by the theme of mentors in Section 6.7.1.6). This aligns with prior work by Ong et al., who discussed that counterspaces can be physical, but may also be more "conceptual and ideological, such as in mentoring and peer-to-peer relationships" [p. 219][Ong et al., 2018].

Overall, preparation and personal practice were an important part of students' job attainment, which bolstered feelings of competence and resulted in more confidence. Peers, mentors, faculty/academic advisors, and family all served to offer navigational capital that helped students to maneuver through the hiring process, teaching them what to expect and/or suggesting resources to study. Furthermore, social capital also played a role, and many students cited professional clubs and organizations such as UPE, SHPE, and NSBE not only offering practice, but also introductions and opportunities to connect with employers.

Furthermore, working on side projects helped to apply more theoretical concepts taught in courses, and many students mentioned they learned better by gaining hands-on experience. When creating a project, they were able to make their own decisions and troubleshoot to get their program up and running, which they reported served their ability to answer technical interview questions better than just drilling down with online coding resources. Such a finding is not entirely unexpected as project work and simulations that tackle real life problems are considered beneficial to skill development [Nagarajan, 2011]. Along these lines, internships and work placement have also been suggested to help students to develop disciplinary knowledge and professional identity in computing [Nagarajan, 2011, Kapoor and Gardner-McCune, 2019].

In the case of my participants, receiving at least one job offer and/or completing internships, did indeed reinforce computing identity. Students reported these experiences made them feel more confident in themselves and their abilities (as referred to by the sub-construct of performance/competence). Receiving recognition on tasks during hiring or in the workplace also served to boost their belief in themselves, and also made them feel more accomplished. Given that recognition has been shown to be particularly important in developing disciplinary identity [Hughes et al., 2021], interviewers and educators should consider offering specific praise for performing well on assignments, projects, or on questions.

While each individual may vary in their strategies and approach to the hiring process, and there may be a lot of variability from company to company, the ways students, and particularly minoritized populations, activated and extended CCW to attain a job in computing speaks to a lot to the efficacy of underlying support mechanism. As discussed, multiple options aid in the development and reinforcement of computing identity, and that can encourage students throughout their time at universities and during hiring. In the section that follows, I further discuss some of the implications of students' suggestions, and recommendations on additional ways to improve preparation and the hiring process.

6.8.2 C6RQ2: Recommendations to Improve Student Preparation and Hiring

Evident in this work is the ongoing concern that although universities and industry are trying to broaden participation, there is still a long way to go to resolve current inequities. Corporate efforts to increase recruitment of minoritized students from venues such as the Grace Hopper Celebration of Women in Computing or NSBE conferences may improve diversity in the applications received, however, to increase persistence and retention, it may be important to cultivate more inclusive thinking in the field, and to reform hiring and workplace practices that may continue to deter applicants. In the sections that follow, I provide specific recommendations for academia, industry, and for students.

6.8.2.1 Academia

Given the need to create more inclusive educational and workplace environments, universities should consider embedding empathetic behaviors and mentalities early on in students, teaching them to embrace diversity, and the importance of giving all students the chance to take on leadership roles and to gain practice with different tasks. As a small start, group projects, particularly in software engineering courses, could encourage revolving roles that allow each team member to gain experience working on different components, with differing levels of responsibility. This requirement could ameliorate concerns mentioned by females that they are often relegated to secretarial roles or tasks that may be less critical to outcomes. By promoting inclusivity, academic institutions can advance mindsets geared towards equity which will shape the future workforce, and those later involved in the hiring process.

Students also suggested they would prefer supplementary practical examples. Given that many concepts are abstract, and can be challenging, offering increased applications may help with knowledge transfer and understanding [Ryoo et al., 2015]. Prior studies have demonstrated how making computing content accessible, and relating CS to everyday life can be a valuable pedagogical approach [Ryoo, 2019]. Moreover, providing students with more opportunities to gain experience through projects, which can also serve to develop their problem solving and digital portfolios, is something that could be incorporated into coursework.

In addition, offering a class on technical interview preparation is something students note would be beneficial (Section 6.7.4.8). Particularly for students that work, or that have other outside commitments (further described by the category of time demands of preparation in Section 6.7.5.3), creation of a designated course could alleviate some of the burden and stress, and would help to level the playing field. Giving opportunities to solve challenging problems on a whiteboard, teaching interview skills, and offering students opportunities to practice with mock interviews could be beneficial to improving communication abilities and could enable them to test out different strategies in a low pressure environment.

Previous work integrating a practical course as part of the Bachelor of Information and Communications Technology (BICT) degree at a university in New Zealand yielded some positive insights [Snell-Siddle et al., 2014]. The course itself offered students information about what to expect from the interview process, typical formats and questions, and other tips on presentations and non-verbal communication.

Then, the course included a role play session, simulating technical interviews. Although initially the students reported feeling anxious before the interview role play, as the sessions wore on the students noted they began to apply the lessons learned from the preparatory process and to feel more confident in their answers. As weeks passed after the fact, and the students reflected on the simulation experience, they noted how beneficial it had been. Although this is not a component typically offered with computing degrees around the world, it provides a useful model to what such a course, or addendum to a capstone project could look like.

While changes to the curricula may take time, in the short term, universities should consider offering tech specific career support to reduce uncertainty and to help students refine their interview techniques. Furthermore, departments should also inform students early on in their academic careers what hiring entails in the field, and they could provide information about resources that can be used to study for technical interviews. Finally, I suggest they make students aware of the value of internships, and describe which professional organizations are available, and the benefits of community development and preparation.

6.8.2.2 Industry

Apart from the moral, financial, and innovation value of building diverse teams in a workplace, considering the intersectionality of individuals can play a critical role in leveraging the assets of men and women that self-identify as a racial/ethnic minority [Catolino et al., 2019, Vasilescu et al., 2015, Yarger et al., 2019]. Employers should appraise the opportunities to harness the unique capital that different people can contribute. As mentioned in Section 6.7.1.7 (which described the theme of communication), soft skills can be valuable to a company. For example, a multi-lingual employee may possess better developed skills to interact or negotiate with clients, since they may have served as interpreters that translated phrases or culture to their own parents or relatives [Ahmed et al., 2013, Trauth et al., 2012, Stevens and Norman, 2016].

Industry must also assess its role in perpetuating inequities and how they can create a more welcoming atmosphere (an obstacle described in Section 6.7.5.5). While change is required at multiple levels [Windley and Pan, 2017, Thomas, 2017], I primarily focus on hiring in this work. In the context of technical interviews, a first step is diversifying the engineers or managers that are present and asking questions. This shift may encourage intersectional confidence, as men and women of diverse backgrounds see others like them. Furthermore, consideration should be given to interviewers' demeanor and how they speak to candidates, to aid with anxiety management in the interviews (6.7.5.4).

Also, although English may be required on the job, and candidates may be able to speak and understand it, students reported interpreting interviewers' accents could pose a problem in understanding questions asked during interviews. As such, trying to decipher what was being requested, on top of dealing with an already stressful technical interview challenge, can be especially challenging. Previously, the difficulty of decoding spoken language has been described as a dual challenge not only for listeners trying to interpret the speech of others with accents which differ from their own, but also in terms of understanding the different ways words are said as either part of a sentence or in isolation [Paran, 2012]. Paran has mentioned that listeners at all levels may struggle to recognize words, and that there are there may be less ambiguity with written words. As such, a simple solution in regards to technical interviews, may be for all employers to write down the question or prompts for all job candidates, so that they can reflect on finding a solution, rather than needing to decipher what is being said.

Furthermore, even before hiring begins, companies should be transparent in what candidates can expect. Being upfront about the steps in the process, how long it may take, and what kind of technical components will be expected can ensure that all applicants start on equal footing to reduce uncertainty (Section 6.7.5.1). Similarly, offering study guides that restrict the topics candidates may encounter or need to review, could reduce some of the burden for students that have limited availability to study based on other commitments, as described by the obstacle of the time demands of preparation (Section 6.7.5.3).

Long term, industry should consider refining or replacing the current hiring process altogether. Although it may be important to ensure all candidates possess the hard and soft skills needed for a role, current practices may not be the best method, as described by obstacles mentioned in the category of interview techniques (Section 6.7.5.2). To be mindful of how much preparation is needed, companies should instead think about offering more take home assignments, or providing applicants the opportunity to talk through their solution to problems recently encountered at the company. In tandem, they could offer training during onboarding for all employees, which could serve to provided the added benefit of all recent hires being familiar with their stylistic, algorithmic, and system design preferences.

6.8.2.3 Students

Meanwhile, students should be cognizant that it can take time to find a position, and they should try to manage their expectations. This can help to reduce the stress they may feel during interviews and within the hiring process, as discussed by the category of anxiety management (Section 6.7.5.4). However, job candidates have the tools to succeed, and they are capable. Participants that had already attained a job in this study emphasized that it was helpful to apply past experiences when solving problems during interviews. As challenging as it can be, speaking through each thought while solving, and describing the preferred approach can help to find a solution or to recognize errors. It is also acceptable to ask questions to interviewers, and it is critical to ask for clarification when necessary.

Preparation is important to answering the types of questions asked during the hiring process, and can help to improve students interview techniques (Section 6.7.5.2. As other scholars have described [Behroozi et al., 2019, Kapoor and Gardner-McCune, 2020, Wyrich et al., 2019], online coding resources such as Leetcode, Geeks-ForGeeks, and HackerRank can also be assets to improve problem solving ability and speed. In addition, books such as Cracking the Coding Interview [McDowell, 2015], can provide further opportunities for technical understanding and growth. Furthermore, it can be useful to lean on social support throughout the hiring process.

6.9 Validity and Reliability

This study upheld the standards of validity and reliability, as guided by the recommendations for quality in engineering education by Walther et al. (2013). To ensure procedural validity, detailed accounts of data collection, analysis, and all procedures and decisions were kept. During the analysis itself, a highly iterative process was used to define the categories of description. Additional individuals contributed to this work and were involved in different validation aspects such as independent label discovery, parallel excerpt grouping, and negotiation on the categories to ensure findings were strongly supported in the quotes taken from the transcript data.

The outcome spaces that emerged as the visual representation of the categories of description, were based on consideration for the collective participants' perceptions of the phenomena, rather than focusing on individuals to ensure communicative validity. For the themes that encompassed one or more categories, a minimum cutoff was used to determine the presence of each, and this value was five or more quotes centered on similar topics. To establish pragmatic validity, and to ensure our results would be useful and applicable to the target demographic, different aspects of the hiring process in computing were considered when defining the interview protocol. Purposive sampling was also used to ensure a diverse mix of students were obtained, who all have already completed technical interviews and successfully attained a job.

6.10 Limitations

While the research addresses an evident gap in literature, there are several limitations. First, the excerpts examined were only portions of the full transcripts, so although context was provided, it was impossible to capture the experience described during the interview in its entirety. In addition, according to Ritchie et al. [Ritchie et al., 2013], the biggest threat to the validity of interviews is that by nature it is an unnatural setting, which can lead to a lack of rapport/trust with the interviewer, impacting the outcome of the findings. Although it may be impossible to overcome this completely, steps can be taken to mitigate its influence and to make the participants feel comfortable [Salzman, 2014]. In this case, interviews were conducted at the respondent's preferred location, using Zoom to communicate. Furthermore, these interviews started with casual talk to get to know each other. Such steps have been shown to make the respondent feel more at ease.

Additionally, the individuals interviewed elected to share their stories and experiences, and they may not include the same scenarios or experiences of those who did not opt to speak with me. Furthermore, it has been pointed out by Bucks and

Oakes that often phenomenography tends to be limited "only captures the participants' understanding or experience at a specific point in time" [Bucks and Oakes, 2011]. Along these lines, it should be disclosed that the interviews were conducted in the Fall of 2020, a time in which the COVID-19 pandemic may have impacted or altered the way the hiring process was conducted, and may have resulted in additional disruptions for the students interviewed. While often participants described a range of experiences over different periods, on site visits were frequently restricted in lieu of virtual alternatives.

6.11 Conclusions

This research describes the various pathways and perceptions of experiences for job attainment in computing, with a focus on populations underrepresented in the field. This work contributes to the body of knowledge by not only detailing students' experiences with the hiring process, but is also unique in its focus on the pathways of minoritized job candidates. The support mechanisms described in the outcome space for C6RQ1, need to be encouraged and celebrated. In addition, as highlighted by the outcome space of C6RQ2, there is more that industry, academia and students can do to overcome obstacles with preparation and the hiring process. As perceived by students, and possibly faculty as well, largely the burden to change the process of technical interviews falls on industry. However, until such changes occur, institutions and students need to be ready to tackle current systems.

Universities should make students aware of the expectations required to obtain a job early on in students' careers and should also promote organizations that may serve to help students find their own community. While some suggestions are a bit easier to implement (e.g., educators giving more practical examples), and others that may take considerable time and effort (e.g., creating courses to aid in preparation), universities should consider the value these could offer. Not only could these recommendations aid in students' preparation for a career, but they could also help them to apply and practice more theoretical concepts taught in classes. Yet, students must also do their part, and they should be sure to study and gain familiarity with the topics they are taught. While it may be a challenge to overcome imposter syndrome, they are capable of succeeding. During interviews they should also apply past experiences, and manage their own expectations, as the hiring process at each company may be quite different. Ultimately, broadening participation is a process, and to truly achieve equity in computing and to promote inclusivity, change needs to occur not just at the industry level, but also within universities, and in the mindsets of future workers in the field.

CHAPTER 7

CONCLUSIONS AND RECOMMENDATIONS

In this chapter, I will provide an overview of the studies conducted in Section 7.1, along with the results, brief answers to the research questions, and significant connections between them in Section 7.2. Then, some of the key suggestions made throughout the dissertation to improve student preparation for technical interviews, and the hiring process in computing are summarized for students in Section 7.3, academia in Section 7.4, and industry in Section 7.5. While this does not include a complete recapitulation, it does highlight several of the major recommendations. Finally in Section 7.6, the directions for future work are discussed, and then the last remarks are given in Section 7.7.

7.1 Summary of Studies

This dissertation focused on understanding the hiring process in computing, and pathways to job attainment. In particular, it explored the implications on underrepresented groups in the field. This work was guided by four research questions, which were established to better understand the impacts of technical interviews, and other professional experiences and cultural experiences on students' computing identity, and the inherent capital leveraged to succeed in obtaining a position.

Research Questions:

- **RQ1:** What does the hiring process in computing look like from both the applicant and industry perspective?
- **RQ2:** How do cultural experiences impact technical interview preparation?
- **RQ3:** How do technical interviews, and other professional and cultural experiences impact computing identity?

- **RQ4:** What are students' experiences with the hiring process in computing?

The dissertation involved a SLR (Chapter 3) to define the hiring process and to answer RQ1, followed by an an explanatory sequential design. The first phase of the explanatory sequential setup included a survey conducted to evaluate students' background, perceptions, and experiences, and was used to answer RQ2 (Chapter 4) and RQ3 (Chapter 5). Afterwards, the results of this survey were analyzed, and used to identify candidates for follow up interviews. Then in the second phase, to answer RQ4 (Chapter 6), a discursive phenomenography was applied to examine how students succeeded in attaining a position in computing and their conceptualization of the experience.

These studies demonstrate that the hiring process in computing is distinct, relative to other fields, and that technical interviews are perceived as particularly onerous. Students from different gender, racial, and ethnic groups have divergent commitments which may limit their availability to prepare for technical interviews, and contributes to continued inequities in hiring. In order to know what to anticipate from the hiring process, and how to study, students report they typically learn less from their universities, and more from other sources. They often use a combination of support mechanisms, and leverage different forms of capital to overcome obstacles, to persist in the discipline, and to succeed in obtaining a position.

7.2 Results and Answers

7.2.1 Summary of Research Findings

The following list summarizes the key contributions of this research, and the chapter that describes each:

1. The hiring process in computing was formally depicted from the perspectives of both job seekers and employers/industry (Chapter 3).

2. Empirical evidence was provided of a link between how early students begin preparing for technical interviews, how much time they spend, and the number of job offers received (Chapter 4)

3. The time students spend preparing for technical interviews varies based on how they self-identified with different gender, racial, and ethnic groups (Chapter 4). The number of job offers they received varied (Chapters 4 and 5). Likewise, contextual influences and personal situations of these students differed (e.g., time spent working in a non-computing job) which may contribute to their availability to practice for technical interviews (Chapter 4).

4. Technical interviews, and other professional and cultural experiences have an impact on students' computing identity (Chapter 5).

5. Despite challenges in school or during hiring, students utilize multiple types of support mechanisms to obtain a job in computing, including: intrinsic characteristics, capitalizing on experience, community, preparation, and organizational (Chapter 6).

6. There are five major categories of obstacles students described encountering in relation to the hiring process in computing: uncertainty, interview techniques, time demands of preparation, anxiety management, and improving inclusivity. To remedy these problems, three agents for change — industry, academia, and students — can each serve different purposes to improve hiring preparation and performance (Chapter 6).

7. Students' intersectional backgrounds contributed to how they navigated social and hiring interactions, and influenced their preferences, motivations, and

belonging in school and in the workplace. Professional organizations often served as counterspaces for minoritized students to challenge their sense of marginalization, and to help them prepare for hiring (Chapter 6).

7.2.2 RQ1: What does the hiring process in computing look like from both the applicant and industry perspective?

Although hiring may vary from company to company, the process broadly involves preparation, the interview itself, and feedback and decisions. In terms of preparation, employers/industry usually spend this phase focused on recruitment, including discovery and initial contact. By comparison, job seekers, who are considered applicants at this phase, are concerned with studying and applying for the role.

The interview phase may include any number of rounds of in situ or on site evaluations, and technical challenges are often employed for computing roles. Job candidates may be asked to complete screening coding tests, take home assignments, to solve problems on phone or video calls, or to demonstrate programming skills in real-time via whiteboards, text editors, or using pencils and papers. In addition, they also are frequently asked questions about foundational knowledge/computing fundamentals. Similar to other fields, behavioral components are also typical, and may entail assessing the candidates' personalities or prior experience.

The feedback and decision phase of the hiring process may also include additional contact, selection of a job candidate, and a decision that results either in a formal offer, negotiation, or a rejection. However, many candidates report poor communication by companies as a major concern, often uncertain about what to expect in the process, unaware of where they stand throughout, adversely affected by rude or hostile interviewers during technical interviews, and stressed when they do not hear back about their status. Yet, when treated as colleagues during technical challenges, and provided regular status updates, the overall impression of the company is far more positive.

Literature on the hiring process in computing is also largely focused on knowledge deficiencies or skill gaps rather than the process itself. Furthermore, limited literature attempts to address making hiring in computing more inclusive or initiatives to improve diversity, despite inadequate representation of women, Black/African Americans, and Hispanic/Latinx workers relative to their proportional presence in the population of the U.S. As such, future researchers should examine the impacts of technical interviews, and particularly how they affect populations already minoritized in the discipline. In addition, while the media and companies have made the push to encourage applying to jobs in technology roles, and may be taking steps to broaden participation, these aspirations are incongruent with the demographics present in all professional levels (e.g., entry-level, management) of companies in computing [Swartz, 2017, Hall Jr and Gosha, 2018, Google, 2020, Facebook, 2020, Kraus, 2020]. Furthermore, barriers remain which impede the progress of broadening participation, and often consideration of how hiring and technical interviews may perpetuate inequalities is neglected.

7.2.3 RQ2: How do cultural experiences impact technical interview preparation?

Students' preparation for technical interviews may begin before a job application is ever submitted. To prepare, students most often report using online coding resources (reported by 20% of all students that had at least one technical interview). Despite employer expectations, and recommendations in study guidebooks (e.g., Cracking the Code [McDowell, 2015]) that preparation should begin months or year in advance, most students cited that they began preparing one week or less before the interview (47%), or two weeks to one month beforehand (42%). Typically the students reported spending one to five hours preparing for these interviews (47%).

In the sample, White students began preparing earlier for technical interviews, spent more time preparing, and received more job offers. Females also spent more hours preparing on average, and received more job offers. However, females, Black/African American students, 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. When considering the support mechanisms students may leverage to overcome obstacles (e.g., having friends in computing or a home environment supportive of computing), there were also differences between students that identified with different gender, racial, and/or ethnic groups. In general, these results emphasized the larger issues in existing hiring structures, and demonstrated the importance of not treating students as a monolith.

7.2.4 RQ3: How do technical interviews, and other professional and cultural experiences impact computing identity?

Students reported a number of positive and negative experiences related to technical interviews. Although students could select more than one choice since they may have had multiple encounters, 60.29% of students who had at least one technical interview noted that "The interviewer was kind and/or respectful." Unfortunately, 31.14% also reported feeling "Like I was not prepared." Students often had concerns related to the questions they were asked and 18.0% of students noted they were "too difficult" and 16.86% said they "were not relevant for the position."

Among other findings, students that did not have positive experiences with technical interviews had a reduced computing identity, but unexpectedly, facing discrimination during technical interviews had the opposite effect. Social support may play a role. Having friends in computing bolstered computing identity for Hispanic/Latinx students, as did a supportive home environment for women. Also, freelance computing jobs increased computing identity for Black/African American students.

7.2.5 RQ4: What are students' experiences with the hiring process in computing?

Phenomenography was employed to understand students' conceptions of their experiences with hiring in computing and job attainment. Overall, students reported there was a lot of variability in what they faced, and that each company had very different expectations and processes. Many students also stressed that even during particularly challenging interviews or instances where they failed to perform well, they took the experience as a learning opportunity that was beneficial for their development. Such encounters spurred them to study more and to keep going.

Interestingly, students held mixed feelings on the inclusivity of the field and during hiring. Although many students reported there was still a long way to go to to improve diversity and create a welcoming atmosphere, or that them or their friends had experienced sexism and/or racism, they seemed accepting of such inequities and behaviors, and often tried not to let such issues get to them or deter them from persevering in the field. Consistent with the findings of other researchers [Mahmoudi, 2017], students reported that most frequently interviewers for the technical components were White or Asian males. If females were present at all in the hiring process, it was most likely the recruiter or human resources manager. However, when encountering others that identified with the same race, ethnicity, or gender, they often were more comfortable engaging and felt more favorably about the company.

Students reported that although certain courses were beneficial (e.g., programming and data structures), primarily their coursework was insufficient in helping them to prepare for the hiring process or the workplace. Instead, they reported they often were educated about what to anticipate and developed the skills they would need by leaning on their communities. Computing organizations, and particularly those with racial/ethnic ties such as SHPE or NSBE, proved instrumental in helping minoritized students to prepare for the hiring process, to build their sense of belonging, and to serve as sounding boards when faced with micro- or macro-aggressions. The students used online coding sites, or worked on personal projects to hone skills. Furthermore, they also leveraged many internal attributes to succeed in their pathways to a career, such as their own motivation, and pertinacity in the face of setbacks or obstacles. Although several spoke about being under-prepared or having imposter syndrome when they started the interview process, attaining a job did help to increase their confidence and ability to see themselves as a computer scientist (or engineer, information technologist, etc.).

7.3 Recommendations for Students

The hiring process in computing can be a stressful and demoralizing experience. Such feelings are common, and many students also struggle with imposter syndrome, as described by the participants in Chapter 6. However, students are capable of succeeding, and they should leverage the tools and support mechanisms they have to navigate through school and the hiring process. While it can take time to find a position, perseverance is key. In addition, students should try to manage their expectations, as interviews may vary wildly between companies.

While reforming the technical interview process may be necessary, until such a shift occurs, students should be conscientious of the fact that they will need to study in advance and prepare for the hiring process. Online coding resources such as LeetCode or HackerRank can be assets to improve problem solving ability and speed [Behroozi et al., 2019, Kapoor and Gardner-McCune, 2020, Wyrich et al., 2019]. In addition, books such as Cracking the Coding Interview [McDowell, 2015], can provide further opportunities for technical understanding and growth. For students that prefer more practical applications, completing side projects or participation in hackathons may be preferable ways to strengthen skills.

Also, knowledge is power, and universities' career services and club/organizations on campus can be useful tools for learning about what to expect in the interview process, and in gaining experience with mock interviews. Future job applicants should also be aware that GitHub can be a valuable avenue for demonstrating programming skills [Nagaram, 2015]. However, it is not just the quantity of commits that matters, but also the quality, and commenting can be important. Recruiters have demonstrated a predilection for seeing clear and understandable language.

Finally, it is helpful to apply past experiences when solving problems during interviews. As challenging as it can be, speaking through each thought while solving and describing the preferred approach can help to find a solution or to recognize errors. It is also acceptable to ask questions to interviewers, and it is critical to ask for clarification when necessary.

7.4 Recommendations for Educators and Academia

While academic institutions are not meant to serve as trade schools, this does not mean that educators and administrators should neglect opportunities to encourage their students to put their best foot forward professionally. Along these lines, one of the simplest suggestions to implement, would be to ensure that departments inform students early on in their academic careers what hiring entails in the field, to suggest internships and joining professional organizations that may assist with community development and preparation, and to provide information about resources that can be used to study for technical interviews. It is also imperative to think about how improvements to curricula can serve to assist with knowledge transfer of material covered, to ensure students understand fundamentals and theories, and to promote persistence of all students enrolled.

Previous work in both academia and industry have demonstrated that programming and software testing are knowledge deficiencies for students and newly hired software developers [Radermacher, 2012, Radermacher and Walia, 2013, Garousi et al., 2019b]. However, in a previous assessment in which I used web scraping and natural language processing to analyze job postings in computing, both were cited highly by employers, suggesting they are important to many positions [Lunn et al., 2020]. Accordingly, given the demand by industry, and that prior literature has described them as issues, these may be areas that require additional exploration and for which universities may want to consider placing additional emphasis or adjusting their current pedagogical approach. Based on prior work, students' system testing skills are particularly poor, and it has been demonstrated that students may be unable to properly use test coverage tools [Radermacher, 2012]. Students mention they would like institutions to spend more time teaching them about testing their code. In addition, it is recommended that testing be taught alongside introductory programming lessons to adjust their mindset early, and to encourage students to develop test cases and debug errors throughout the coding process. Along these lines, students would also prefer less emphasis on theory, in general, and more practical examples.

Furthermore, as emphasized by qualitative interviews with students in Chapter 6, offering technical interview preparation, or a course to prepare for the hiring process would be beneficial. Particularly for students who work, or who have other outside commitments, creation of a designated class could alleviate some of the burden and stress and would help to level the playing field. Giving opportunities to solve challenging problems on a whiteboard, teaching interview skills, and offering students opportunities to practice with mock interviews could be useful to improving communication and could enable them to test out different strategies in a low pressure environment.

In part, it is difficult for universities to adequately prepare students if their own staff are unaware of what the technical interview process entails. Previous research has demonstrated that very few CS professors at Historically Black Institutions may have experience with technical interviews themselves [Hall Jr and Gosha, 2018]. Accordingly, they are unable to understand the components required nor the anxiety they can induce. While this work may have been conducted at a HBCU, the principles are likely true for many professors at all universities. Offering faculty workshops and simulations of hiring could prove beneficial to understanding what job seekers encounter. In turn, this could provide insight into how they can better assist their students and could generate ideas to modify course design to address shortcomings.

7.5 Recommendations for Industry

Hiring in computing can be an extensive process for job applicants that necessitates significant preparation and that also requires substantial effort from employers to find the right candidate. The assessments themselves are usually lengthy and may consist of multiple rounds requiring programming on demand. Using coding tests as part of technical interviews does present benefits for employers, such as offering a lower cost to screen candidates and having measures to distinguish between talent and credentials [Shibalayeva and Galicia-Almanza, 2017].

However, these intense, high-pressure hours or days can induce high levels of stress, which may affect candidate's performance [Behroozi et al., 2019]. Moreover, having to solve a problem in real time, while also talking through a solution can be challenging, increasing candidates' cognitive load and reducing their own abilities for self-reflection [Behroozi et al., 2018]. Another caveat is that technical interviews may neglect to assess testing or debugging skills, which is something often reported problematic for new hires [Radermacher, 2012, Radermacher and Walia, 2013, Shibalayeva and Galicia-Almanza, 2017, Garousi et al., 2019b]. There are other pitfalls as well, such as placing greater emphasis on technical skills may disregard others with valuable workplace contributions, such as communication skills to relay ideas to non-technical individuals [Behroozi et al., 2019, Behroozi et al., 2020a].

Some alternative methods for assessing skills have been proposed in the literature. However, options such as standardized performance tests may entail considerable effort to create and to properly validate. Instead, companies could focus on candidates that demonstrate a basic understanding of programming or computing concepts and an ability to learn. Prior work suggests that just understanding the principles behind object-oriented development is sufficient for developers to learn new languages in two weeks [Tockey, 2015]. Therefore, I recommend that employers consider placing less emphasis on abstract coding or computing questions during hiring and instead ask about prior projects, coupled with an increased investment in more training during onboarding. This will ensure that all new employees begin with a level playing field and acumen on the company's stylistic, algorithmic, and system design preferences.

While I acknowledge this suggestion may take time to implement, there are concrete steps that employers can take in the meantime. Given the impact that interviewers have on candidates during the process, employers should consider offering training to hiring managers and employees involved during hiring. Interviews should try to treat job candidates as colleagues rather than making the technical interview feel like an interrogation. In addition, employers should be transparent about where candidates stand throughout the process. Also, early in the hiring process or even beforehand, it would be advantageous for employers to share what they are looking for and expect. While they do not need to give an exact template, being clear about the types of skills desired, what applicants should anticipate during the interviews, and even offering practice tests and preparation guides will help to make the process more equitable, irrespective of prior experience.

To broaden participation in computing, it is also necessary to recruit a diverse set of candidates and to consider inclusive practices supportive of marginalized groups. Even before hiring begins, employers should seek to offer career mentoring or internships opportunities to underrepresented groups to encourage occupational trajectories in computing [Charleston, 2012, DuBow, 2014, Windeler and Riemenschneider, 2013]. Alternatively, co-operative education programs (or "co-ops") are similar to internships, but typically are longer and involve a partnership with an educational institution to offer academic credit for work completed with a company [Tyler, 2015]. Although it may require a greater investment of time and resources, co-ops lead to job candidates with improved preparation and technical acumen. Furthermore, purposeful leadership and placing women and/or minorities as members on industry boards can bring unique perspectives, leverage diverse human capital, and could encourage representation of others within the company [Sandgren, 2014].

In the interview itself, it may be important to consider practices that ensure a candidate has the capability to perform the job, without requiring intensive practice to prepare. Whether a candidate is fresh out of school or more advanced, they should be treated the same, and the approach should be equal. As such, rather than offering a rigorous programming test to assess their abilities, a better approach could be to ask questions or problems that employees at the company recently solved. This method ensures that irrespective of the candidate's experience level, they can demonstrate their approach and problem solving acumen in a concrete way to the types of things they would need to do in the role [Neville-Neil, 2011]. Also, no matter how senior, all levels should be able to solve all questions from the more simple to those involving greater complexity. After it has been established that the candidate does possess the foundations to perform the job, there are other ways to gauge skill that could be more equitable to assess hard and soft skills like creativity, critical thinking, and communication.

7.6 Directions for Future Work

While this research contributes to the broader body of knowledge about computing students' experiences with technical interviews and job attainment and particularly those of women, Black/African American, and Hispanic/Latinx students, there is still much to be explored. In the future, it would be advantageous to gain a broader look at preparation, hiring experiences, and job attainment from the additional perspectives (e.g., seasoned employees, employers, and student groups and organizations already offering training). It would also be valuable to understand what types of professional development activities and experiences in universities and the workplace are the most efficacious at developing computing identity and encouraging persistence of minoritized populations.

One research study could examine the experiences of employees working in computing roles at various time points in their careers (e.g., within the first year, between one to ten years, more than ten years). Employees just beginning their career may have further insight into hiring, and the factors that did and did not work during onboarding. Additionally, by delving into more seasoned employees' experiences, insight could be gained about what factors drive endurance and achievement in the workplace. Also, learning about mentoring opportunities, ongoing training, or other initiatives that positively influence feelings of belonging from employees at different stages could provide companies with practical strategies to create more inclusive environments.

In addition, speaking with employers could offer a more holistic look at current hiring practices. Interviews with hiring managers and/or recruiters may provide a unique perspective on what they expect from applicants and better ways to prepare for these roles. Such information would be useful for universities to consider to better support their students, to establish helpful programs or pedagogical techniques that may assist with career training, and to reconcile knowledge deficiencies.

Furthermore, since many students interviewed mentioned the programs established through student clubs and organizations (e.g., UPE, NSBE, and SHPE) served as the greatest assets to discover how to prepare for hiring and gave them support to persevere, it would be useful to examine which activities offered had the greatest effect, and why? Exploring ways to engage students that identify with different gender, racial, and ethnic groups, studying the impact of specific initiatives, and assessing how these groups successfully reconciled constantly changing demands in the field with already developed material could be illuminating. Distinguishing what works could allow other clubs and organizations (or even departments) to implement similar options.

Finally, going forward, it would be worthwhile to compare performance in technical interviews and in the workforce when considering applicants of different paths, e.g., graduate of a university in a computing discipline versus self-taught programmer versus bootcamp graduate. Given that different avenues may lead to the development of different types of knowledge and skills, such research could yield a wealth of additional information. In turn, these findings could be used to drive change both in academia and industry.

7.7 Final Remarks

This work contributes to the body of knowledge by providing empirical evidence of what hiring in computing entails and the inequity of process. It further describes the impact of technical interviews and other professional and cultural experiences on students' computing identity. Additionally, insight is given into the disparate experiences of students' preparation and the hiring process in computing. Rather than treating all job applicants as a monolith, this research placed a spotlight on women, Black/African American students, and Hispanic/Latinx students. Intersectionality was also applied to further highlight the nuances of experiences, the compounded issues faced by women of color in their pathways to a career, as well as how they dealt with such instances. Employing a mixed methods approach, this dissertation included a range of methodologies, including a systematic literature review, descriptive and statistical analysis of a survey, and a discursive phenomenography. The analysis emphasized the unique capital that each employee can contribute and encouraged companies to consider these assets during hiring and to think about how they could be harnessed in the workplace.

Beyond the obvious moral benefits, establishing gender, racial, and ethnic diversity on teams has the potential to broaden perspectives and to improve innovation and companies' bottom line. However, it is vital to create environments where all employees feel like they belong, where they are comfortable speaking, and where they can play to their strengths. As this work demonstrated, and as described by the community cultural wealth model, it is beneficial to leverage the knowledge, skills, abilities, and contacts individuals can contribute. For example, companies should capitalize on the linguistic capital a multi-lingual employee may possess. Having had to translate phrases or culture to non-native speaking family members could make them more adept at communication with clients and may enable them to better describe products or software [Ahmed et al., 2013, Trauth et al., 2012, Stevens and Norman, 2016].

It is my hope this dissertation will demonstrate that students have the tools to succeed and can offer unique perspectives. In addition, I want to raise awareness of the problems inherent with hiring in computing currently, and how it may further perpetuate inequalities in the field. Striving to create more inclusive interviews and workplaces requires meaningful action and more than just voicing a commitment to change. While it may take time to refine or replace the present hiring practices, doing so is crucial. Companies are entitled to be selective, but while technical interviews claim to filter out candidates that lack in competence or basic skills, they may also be exclusionary to more diverse candidates. These potential employees may have the abilities, but just struggle to perform well under the pressure of a whiteboard challenge, or they may lack the time to prepare for that type of questioning due to other commitments.

In addition, I want to encourage academia to consider its role in preparing students for a future in the field and in the development of their graduate employability. Apart from considering the creation of a course, which could offer all students the opportunity to refine their hard and soft skills and transfer knowledge taught in other classes, I implore them to at least raise awareness of industry expectations and resources students can use early in their academic journey. While each company has different requirements and may approach hiring uniquely, learning about the commonalities and providing all students with information can help to level the playing field. Furthermore, to support students' preparation, institutions could establish partnerships with industry to develop mock interviews or mentorship on the hiring process.

It is important to think critically about the factors that have led to current systems, and the lingering impacts of perpetuating practices that are flawed. Technology positions are going to continue to increase, and it is critical to find ways to meet those needs and improve retention, rather than chasing a stereotype or propagating policies or attitudes which may discourage participation. As a community, we must work together to resist hegemonic forces and practices and to establish more egalitarian methods that encourage the persistence and retention of diverse populations in computing.

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APPENDICES

DEFINITIONS

The following definitions are given to provide better understanding of their meaning in this work:

- *Broadening Participation:* The "meaningful actions that address the long-standing underrepresentation of various populations including women, racial/ethnic minorities (African Americans/Blacks, Hispanic Americans, American Indians, Alaska Natives, Native Hawaiians, Native Pacific Islanders), persons from economically disadvantaged backgrounds, and persons with disabilities, in the computing field." [National Center for Women and Information Technology, 2019, p. 7]
- *Code Katas:* Exercises for programmers that enable them to hone their skills and develop their coding ability [Gant, 2019a].
- *Competence/Performance:* A student's self-confidence in their abilities to understand and complete tasks in computing [Taheri et al., 2018].
- *Community Cultural Wealth (CCW):* A theoretical framework developed by Yosso [Yosso, 2005] for researchers to examine how marginalized community can access different types of capital in their individual and collective experiences. Specifically considers Aspirational, Navigational, Social, Linguistic, Familial, and Resistance capital present in communities of color.
- *Computing Identity:* An expansion of the science identity work by Carlone and Johnson [Carlone and Johnson, 2007], and has been previously defined by the sub-constructs of sense of belonging, recognition, performance/competence, and interest [Taheri et al., 2018].

- *Counterspace:* “Academic and social safe spaces that allow underrepresented students to: promote their own learning wherein their experiences are validated and viewed as critical knowledge; vent frustrations by sharing stories of isolation, microaggressions, and/or overt discrimination; and challenge deficit notions of people of color (and other marginalized groups) and establish and maintain a positive collegiate racial climate for themselves” [Ong et al., 2018, p. 209].

- *Cultural Experiences:* The knowledge learned and shared, for which activities, behaviors, and the interpretation of experiences define everyday life [Adelman, 1988, McCurdy et al., 2004, Cultuur, 2014]. Items considered include day-to-day responsibilities (e.g., caring for others) and social support (e.g., home environment, role models, and peers).

- *Data Science:* A broad concept that ”can be generally defined as a multi-disciplinary blend of data inference, algorithm development, and technology used to solve complex problems analytically and to generate business value” [Lovaglio et al., 2018].

- *Disciplinary Identity:* An individual’s identification with a domain and its affiliated community [Hazari et al., 2010, Taheri et al., 2018, Taheri et al., 2019].

- *e-Recruiting:* A process by which individuals are matched with positions via online and off-line strategies and technology [Malherbe et al., 2015].

- *Employee:* A person that works as for an institution, agency, company, organization, business, association, or firm.

- *Employer:* A person, institution, agency, company, organization, business, association, or firm that puts a person (or people) to work.

- *Experience:* The knowledge, understanding, and skills that result from events, activities, and/or interactions with others [Fisher et al., 1997, Peters et al., 2014].
- *Graduate Employability:* Defined by an ability to obtain a job, to maintain that position, and then to find another [Suleman, 2018].
- *Identity:* A complex, context-dependent, and ever fluctuating conceptualization that is rooted in a person's position individually and as a member of different groups [Gee, 2000, Li, 2009, Spears, 2011].
- *Interest:* A student's personal engagement with respect to computing, and includes possessing a passion for studying, practicing, and thinking about computing topics [Taheri et al., 2019, Mahadeo et al., 2020].
- *Intersectionality:* A theoretical framework for exploring the overlapping components of an individual's identities— whether political (e.g., political affiliations), social (e.g., race, gender, disability), organizational (e.g., job title), or circumstantial (e.g., student, parent) [Corlett and Mavin, 2014]. It argues that men and women are not a monolith [Beddoes and Borrego, 2011, Collins and Bilge, 2016, Lord et al., 2009], and describes how "power relations influence social relations across diverse societies as well as individual experiences in everyday life" [Collins and Bilge, 2020].
- *Internship:* A structured partnership in which inexperienced workers or students are given the opportunity to obtain "real-world experience" in their chosen profession with an individual, company, or organization [Janz and Nichols, 2010].
- *Job Applicant:* A person that has expressed interest in being hired, receiving a promotion, or other employment opportunities with an institution, agency,

company, organization, business, association, or firm. Interest may be shown either verbally or via an application.

- *Job Candidate:* An applicant whose qualifications are deemed sufficient for the requirements of a particular job posting, and they are under consideration for the role. Typically they undergo some kind of interview, and then if the person or group of people looking to fill the position feels the job candidate is the best fit and/or will perform well, they will offer them the position.
- *Job Seeker:* A person trying to obtain a role in the industry, or with a particular institution, agency, company, organization, business, association, or firm. May be in the preparation stage, actively applying for positions as a job applicant, and/or a job candidate.
- *Knowledge Deficiency:* Any skill, ability, or knowledge of concept which a recently graduated student lacks based on expectations of industry or academia [Radermacher and Walia, 2013].
- *Latinx:* A gender-neutral term used to describe persons of Latin descent, that considers the intersectionality of social identity [Gamez, 2017].
- *Mentoring:* An intentional pairing between a person with greater experience and skills and another person with less experience and skills in order to help the one with less familiarity on the topic improve their performance, knowledge, and competencies [Trauth et al., 2010].
- *Phenomenography:* The empirical study of the limited number of qualitatively different ways in which various phenomena in, and aspects of, the world around us are experienced, conceptualized, understood, perceived, and apprehended [Marton, 1994, p. 4424].

- *Professional Experiences:* The "interactions, situations, and events individuals encounter while serving in a particular workplace role" [Klein, 2016], and also include skill development (e.g., training/leadership opportunities), defining career goals, and/or networking [Worthen, 2005]. In this dissertation, the definition is extended to include the hiring process for roles, and to specify the development of computing skills (e.g., participating in coding bootcamps or freelance computing-related jobs).

- *Recognition:* The internalized perception of recognition a computing student feels from others such as teachers, family members, and friends [Taheri et al., 2019, Mahadeo et al., 2020].

- *Role Identity:* Suggested to develop along with personal identity, it shapes how individuals perceive themselves in the present and future (e.g., as an engineer) [Paul et al., 2020].

- *Self-efficacy:* An individual's personal belief in their own capability of performing a particular task or behavior to elicit a desired outcome [Bandura, 1986].

- *Sense of Belonging:* A student's feelings of belonging to a computing community or group [Taheri et al., 2018].

- *Social Cognitive Career Theory (SCCT):* A framework used to understand the intrinsic and extrinsic variables that influence an individual's occupational choices and performance [Lent et al., 1994, Lent et al., 1999, Lent et al., 2002, Lent et al., 2011]. Applying Bandura's general social cognitive theory as the foundation [Bandura, 1986], it considers self-efficacy, outcome expectations, and personal goals as central facets for disciplinary interest, vocational decisions, and career development [Lent et al., 2002, Lent et al., 2018].

- *Social Identity:* A type of identity that evolves in relation to societal interaction, communication, groups, and constructed categorizations of attributes and characteristics [Tajfel et al., 1979, Goar, 2007, Bliuc et al., 2011, Johansson, 2015].
- *Systematic Literature Review:* An overview of the present body of literature on a topic that seeks to systematically identify, examine, and synthesize relevant work [Petticrew and Roberts, 2006]. Tests either a unary hypothesis or a combination of related hypotheses.
- *Technical Interview:* Part of the hiring process for a computing position that occurs online, via phone/video call, or on-site/in-person, and that includes any combination of problem solving, logic, live coding, and/or programming tests for job candidates [Behroozi et al., 2020a, Behroozi et al., 2018, McDowell, 2015]

SLR PUBLICATIONS

The full list of publications identified in the SLR, and the categories they were assigned to is described in Table 7.1.

	Interview Preparation	Interview Process	Interview Feedback or Decisions	Skills Needed for Jobs or Skill Gaps Reported	Mentions of Barriers or Improvement Initiatives: Gender	Mentions of Barriers or Improvement Initiatives: Race/ Ethnicity
References	[Hall Jr and Gosha, 2018] [Lara et al., 2019] [Behroozi et al., 2020a] [Behroozi et al., 2019] [Singer et al., 2013] [Raaen and Lauvås Jr, 2018] [Penrod, 2019] [Nagy, 2019] [Konchady, 2016] [Mahmoudi, 2017] [Calitz et al., 2014] [Calitz et al., 2015] [Evans, 2012] [Capiluppi et al., 2013] [Craig et al., 2018] [Grossman, 2012] [Burke et al., 2018] [Gant, 2019b] [Hunsinger et al., 2011] [Jackson, 2013] [Kapoor and Gardner-McCune, 2020] [McDowell and Bavaro, 2014] [McDowell, 2014] [McDowell, 2015] [Mongan et al., 2012] [Marlow and Dabbish, 2013] [Marlow et al., 2013] [Aziz et al., 2012b] [Aziz et al., 2016] [Aziz et al., 2015] [Webb, 2014] [Xu et al., 2020] [Waldrop, 2017] [Poundstone, 2012] [Wynn and Correll, 2018] [Papoutsoglou et al., 2019] [Wyrich et al., 2019] [Yarger et al., 2019] [Sarma et al., 2016] [Wang and Redmiles, 2019] [Whitney et al., 2013] [Nagaram, 2015] [Tyler, 2015] [Sharma, 2014] [Rothman, 2013] [Pierce, 2016] [Rawlings-Goss, 2019b] [Snell-Siddle et al., 2014] [Trauth et al., 2012] [Takalo and Hassan, 2016] [Amadoru and Gamage, 2016]	[Lara et al., 2019] [Behroozi et al., 2020a] [Behroozi et al., 2018] [Behroozi et al., 2019] [Nagy, 2019] [Raaen and Lauvås Jr, 2018] [McDowell, 2015] [McDowell, 2014] [McDowell and Bavaro, 2014] [Capiluppi et al., 2013] [Grossman, 2012] [Gant, 2019b] [Mongan et al., 2012] [Jackson, 2013] [Kapoor and Gardner-McCune, 2020] [Penrod, 2019] [Aziz et al., 2012b] [Aziz et al., 2016] [Aziz et al., 2015] [Wyrich et al., 2019] [Webb, 2014] [Poundstone, 2012] [Rothman, 2013] [Tyler, 2015] [Sharma, 2014] [Rawlings-Goss, 2019b] [Takalo and Hassan, 2016] [Behroozi, 2019] [Ford et al., 2017a] [Blincoe et al., 2019] [Snell-Siddle et al., 2014]	[Penrod, 2019] [Nagy, 2019] [Behroozi et al., 2019] [Behroozi et al., 2020a] [Gant, 2019b] [McDowell, 2015] [McDowell and Bavaro, 2014] [McDowell, 2014] [Mongan et al., 2012] [Grossman, 2012] [Aziz et al., 2016] [Aziz et al., 2015] [Aziz et al., 2012b] [Webb, 2014] [Rawlings-Goss, 2019b] [Tyler, 2015] [Poundstone, 2012] [Rothman, 2013]	[Singer et al., 2013, Lara et al., 2019] [Almi et al., 2011, Ahmed et al., 2012] [McDowell, 2015, Mardis et al., 2018] [Tockey, 2015, Radermacher, 2012] [Radermacher and Walia, 2013] [Radermacher et al., 2014] [Heffernan, 2014, Konchady, 2016] [Nagy, 2019, Raaen and Lauvås Jr, 2018] [Garousi et al., 2019b, Burke et al., 2018] [Exter et al., 2018, Penrod, 2019] [McDowell, 2014, McDowell and Bavaro, 2014] [Mahmoudi, 2017, Gant, 2019b] [Craig et al., 2018, Grossman, 2012] [Capiluppi et al., 2013, Evans, 2012] [Calitz et al., 2014, Calitz et al., 2015] [Papoutsoglou et al., 2019, Aziz et al., 2016] [Aziz et al., 2015] [Mongan et al., 2012, Aziz et al., 2012b] [Jackson, 2013] [Kapoor and Gardner-McCune, 2020] [Marlow et al., 2013] [Marlow and Dabbish, 2013] [Hunsinger et al., 2011, Webb, 2014] [Xu et al., 2020, Waldrop, 2017] [Poundstone, 2012, Ibezim; Ekpereka, 2017] [Wyrich et al., 2019, Wang and Redmiles, 2019] [Sarma et al., 2016, Rothman, 2013] [Tyler, 2015, Sharma, 2014] [Nagaram, 2015, Rawlings-Goss, 2019b] [Trauth et al., 2012, Exter and Ashby, 2019] [Takalo and Hassan, 2016] [Snell-Siddle et al., 2014] [Behroozi, 2019, Exter, 2014] [Ahmed et al., 2015, Aken et al., 2010] [Akdur, 2019, Aasheim et al., 2019] [Dubey and Tiwari, 2020, Moreno et al., 2012] [Rehman et al., 2011, Scaffidi, 2018a] [Zhou et al., 2018, Cerioli et al., 2020] [Peslak et al., 2018, Nagarajan, 2011] [Naiem et al., 2015, Watson et al., 2017] [Patacsil and Tablatin, 2017] [Uzoka et al., 2018] [Florea and Stray, 2018] [Florea and Stray, 2019] [Stevens and Norman, 2016] [Oguz and Oguz, 2019] [Gallagher et al., 2010, Gallagher et al., 2011] [Gurcan and Sevik, 2019, Garousi et al., 2019c] [Garousi et al., 2019a, Hawk et al., 2012] [Hewner and Guzdial, 2010] [Hiranrat and Harncharnchai, 2018] [Jones et al., 2018, Jumabayeva, 2014] [Li et al., 2015, Li et al., 2020] [Liebenberg et al., 2015, Litecky et al., 2012] [Lovaglio et al., 2018, Matturro, 2013]	[Lara et al., 2019] [Behroozi et al., 2019] [Behroozi et al., 2020a] [Mahmoudi, 2017] [Kapoor and Gardner-McCune, 2020] [Evans, 2012] [Grossman, 2012] [McDowell, 2014] [Rothman, 2013] [Whitney et al., 2013] [Wynn and Correll, 2018] [Wang and Redmiles, 2019] [Rawlings-Goss, 2019b] [Blincoe et al., 2019] [Dubey and Tiwari, 2020] [Nagarajan, 2011] [Oguz and Oguz, 2019] [Trauth et al., 2012]	[Lara et al., 2019] [Hall Jr and Gosha, 2018] [Behroozi et al., 2019] [Behroozi et al., 2020a] [Mahmoudi, 2017] [Yarger et al., 2019] [Trauth et al., 2012] [Rothman, 2013] [Rawlings-Goss, 2019b] [Li et al., 2020] [Evans, 2012]
Total Count	51	31	18	93	18	11

Table 7.1: Publications identified throughout hiring process with consideration of skills needed and impact for underrepresented groups

SURVEY INSTRUMENTS

The questions from the survey that are relevant for this research are included in Table 7.2.

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 • Personal Referral • Recruiter • Campus Recruiting • Career Fair • Hackathon or Programming Competition • Contact through Social Media (e.g. LinkedIn, Facebook, etc.) • Contact through Software Development Site (e.g. GitHub) • Through Professional Organization • Through Coding Bootcamp • In Person • General Job Portals/Search Engines (e.g., CareerBuilder, Glassdoor, SimplyHired, We Work Remotely, Indeed) • 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 • Online Coding Resources (e.g. LeetCode or HackerRank) • Preparatory Books (e.g. Cracking the Code) • Self Study of Textbooks • Course Notes or Assignments • Mock Interviews • Projects Outside School/Work • Other (Text entry)	Select All, with Text Entry

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) • Caring for an adult (e.g. grandparent) • Personal recurring health problem (not including common illnesses like a cold or flu) • Other (Text Entry)	Select All, with Text Entry
With which racial and ethnic group(s) do you identify?	• American Indian or Alaska Native • Asian • Black or African American • Hispanic, Latinx, or Spanish origin • Middle Eastern or North African • Native Hawaiian or Other Pacific Islander • White • Another race or ethnicity not listed above	Select All
How do you describe your gender identity?	• Female • Male • Agender • Transgender • A gender not listed • Text entry	Select One, with Text Entry

Table 7.2: Survey questions and responses used in our analysis

SEMI-STRUCTURED INTERVIEW PROTOCOL

The following script was used for semi-structured interviews:

- Script is in black (read word-for-word), main questions shown with bullets and sub-bullets designating potential follow up questions
- Facilitator notes are in red, will not read aloud any of the text in red
- Script potential additions are in blue, will read when applicable

"Hi, my name is ______________. Thank you for participating in this study. Our goal in this interview is to gain a deeper understanding of your experience with technical interviews, what your experience was, and what your impressions were of the company or companies you met with. This conversation is recorded for accuracy.

Here are some things that you should know about your participation: There is no right or wrong answer. We really just want to know what you thought of the hiring process in computing.

Do you have any questions before we begin?"

- How many interviews have you had so far? Note number
  - Overall how would you describe the experience?
- Please tell me how you found any jobs you applied for? Give time to respond before probing more
  - Online job sites?
  - Career fairs?
  - Recommendations from friends?
- When looking for a job, what factors are most important to you? If not covered, can probe more

  - How much does salary factor in?
  - How about finding the work personally fulfilling?
  - How about personal considerations like distance from family?

- Do you speak any other languages besides English? If the answer is yes, ask
  - Which languages?
  - Do you feel being bilingual or multilingual helps or hinders you in computing?
    * Being reflective about the interview, do you think being bilingual helped or hindered with the interview process?

- What made you want to pursue a career in computing? If not covered, can probe more
  - Do you have any **family** working in the field of computing?
  - Do you have any **friends** working in the field of computing?

- Did you talk to your **family** about your decision to pursue a career in computing and did they influence you in any way?
  - Did you discuss the interview process with them at all?

- Did you talk to your **friends** about your decision to pursue a career in computing and did they influence you in any way?
  - Did you discuss the interview process with them at all?

- Please tell me how you prepared for any interviews? Give time to respond before probing more

  - Did you use any online coding practice sites?
  - Do you have a digital portfolio or personal website?
  - Have you completed any side projects?
  - Are you involved in any clubs or groups that might have offered some form of preparation?
  - Did you ever complete a hackathon or coding competition?
- How did you learn about preparing for a technical interview?
- Do you feel your preparation helped or hindered you?
- How long did you typically spend preparing?
  - Why?
  - Change wording based on how many they have had
    * More than **ONE**: Did you ever find your practices change after having more than one interview?
    * **ONE** interview: Did you ever find your practices change after your interview?
- Did you feel your time in school prepared you for what was asked during the interviews?
  - What areas do you feel were covered well?
  - What areas do you wish had been covered more?
  - Is there anything you wish your university had done differently to prepare you for the hiring process?
- Let's discuss your [first] interview. Please describe your experience.

  - What made you apply?
  - How many steps were involved? Please describe the process.
  - What did you like about the process?
  - What did you dislike about the process?
  - What did you learn from the process?
- Please tell me about what types of questions you were asked during the interview.
  - Did you have any initial phone or online screening?
  - What about an on site?
  - Was any coding involved?
    - Did you have to code in front of one person or several?
    - How did that make you feel?
  - Were you asked any questions that seemed odd?
  - How many people did you meet with?
  - How long did the whole interview take?
  - Did you receive an offer? Did you accept? Did you negotiate?
- What do you think was the biggest challenge in your interview?
- Was the recruiter or hiring manager good about relaying information?
  - Any issues or barriers?
  - How long did it take to receive feedback about the job?
  - Was your overall experience positive or negative?

- I would like to hear about your experience with the diversity of the company.
  - Did you notice that the staff and/or interviewers were **female**?
  - Did you notice that the staff and/or interviewers were **Black or African American**?
  - Did you notice that the staff and/or interviewers were **Hispanic or Latinx**?
  - Did you notice that the staff and/or interviewers were **American Indians or Indigenous people**?
  - How did that make you feel?

Only include this section if they have had more than **ONE**

- Let's discuss your next interview. Please describe your experience.
  - What made you apply?
  - How many steps were involved? Please describe the process.
  - What did you like about the process?
  - What did you dislike the process?
- Please tell me about what types of questions you were asked during the interview.
  - Did you have any initial phone or online screening?
  - What about an on site?
  - Was any coding involved?
    - Did you have to code in front of one person or several?

      - How did that make you feel?
  - Were you asked any questions that seemed odd?
  - How many people did you meet with?
  - How long did the whole interview take?
  - Did you receive an offer? Did you accept? Did you negotiate?
- What do you think was the biggest challenge in your interview?
- Was the recruiter or hiring manager good about relaying information?
  - Any issues or barriers?
  - How long did it take to receive feedback about the job?
  - Was your overall experience positive or negative?
- I would like to hear about your experience with the diversity of the company.
  - Did you notice that the staff and/or interviewers were **female**?
  - Did you notice that the staff and/or interviewers were **Black or African American**?
  - Did you notice that the staff and/or interviewers were **Hispanic or Latinx**?
  - Did you notice that the staff and/or interviewers were **American Indians or Indigenous people**?
  - How did that make you feel?

Only include this section if they have had more than **TWO**

- Were there any other interview experiences you had that stand out, either positively or negatively?

- Is there anything you wish was different about the hiring process?
- Do you think the hiring process in computing is different from other fields?
- Did you ever face any discrimination, either during your interview process or during your time in school? If appropriate
  - How did you deal with that situation?
- How inclusive do you feel careers in computing are towards **females**?
- How inclusive do you feel careers in computing are towards **Blacks or African Americans**?
- How inclusive do you feel careers in computing are towards **Hispanic or Latinx individuals**?
- How inclusive do you feel careers in computing are towards **American Indians or Indigenous people**?
- Is there any other information you would like us to know about the hiring process, or your experiences with technical interviews?

Thank you very much for your time and participation. We really appreciate it.

PHENOMENOGRAPHY DATA ANALYSIS

Transcript Analysis

An example of one the transcripts, analyzed in Mendeley is illustrated in Figure 7.1.

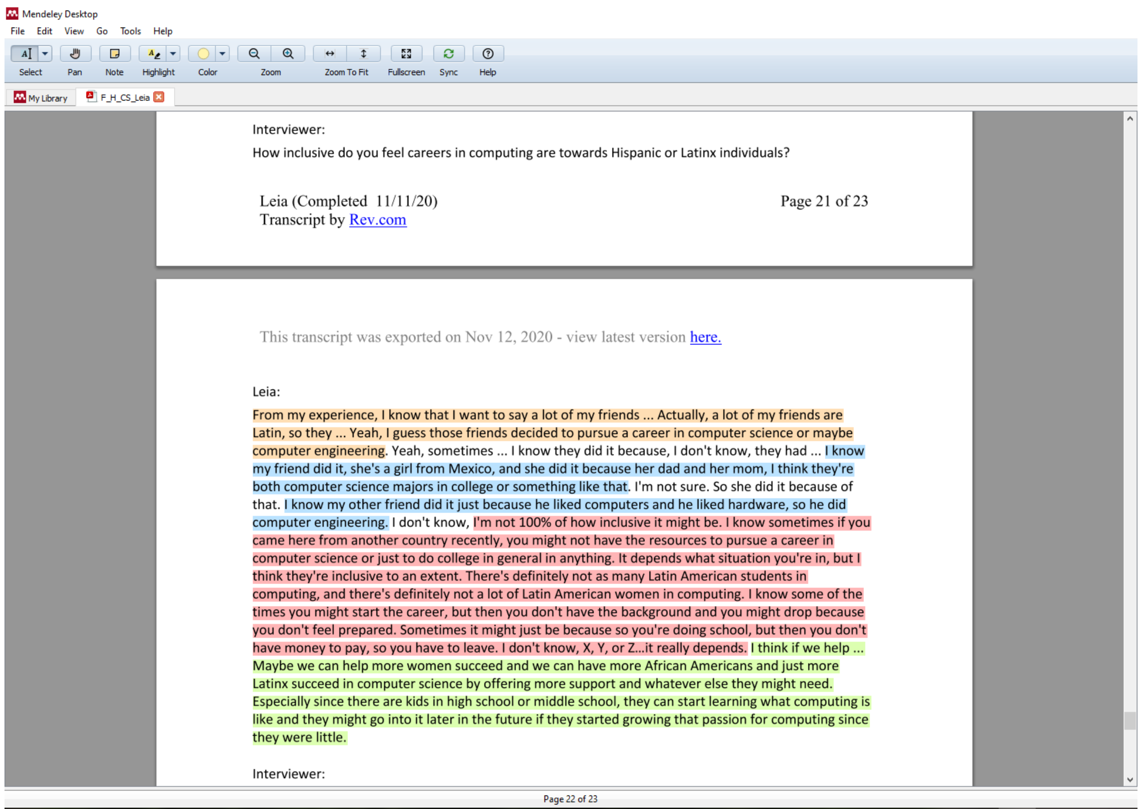

Figure 7.1: Transcripts in Mendeley, highlighting salient excerpts for themes

Pool of Meanings

Trello was used to create a pool of meanings for RQ1 and RQ2. Quotes were organized in a single column and then later moved into another representing the larger theme by the main researcher and another researcher (who assigned them independently and they later negotiated on the categorizations). Examples of the Trello board for RQ1, before quotes were assigned (Figure 7.2), and after negotiations were completed (Figure 7.3) are presented to illustrate the analysis process.

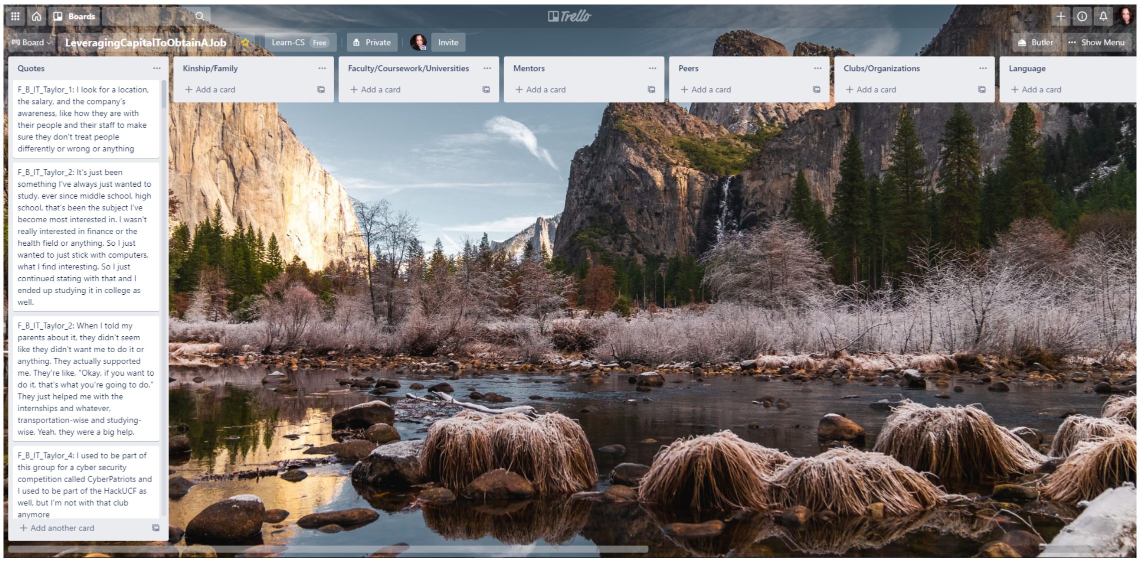

Figure 7.2: Trello board for RQ1, with quotes unassigned

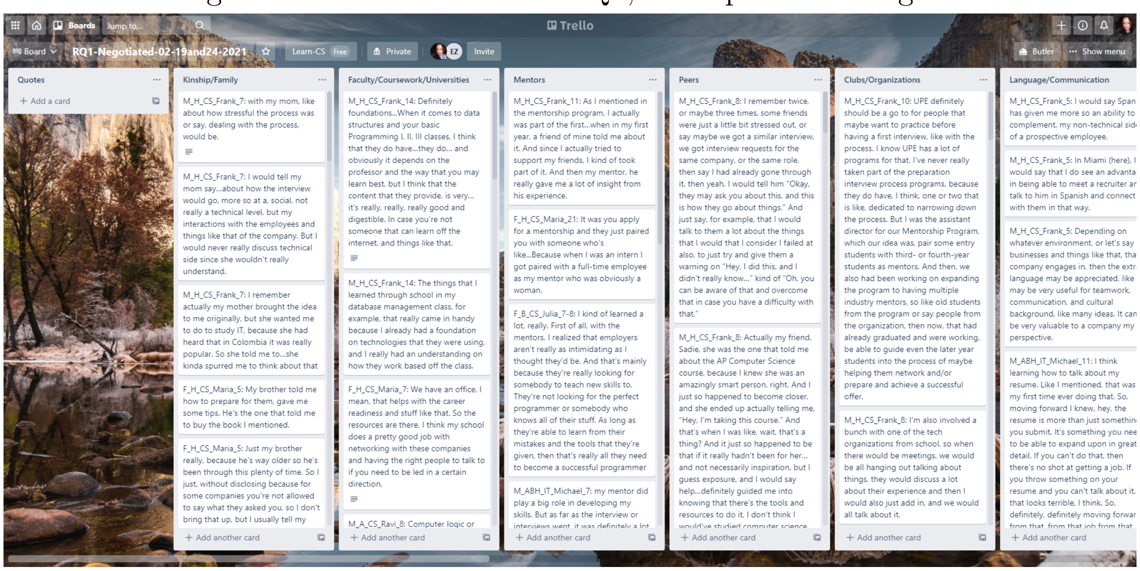

Figure 7.3: Trello board for RQ1, with quotes assigned

VITA

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PUBLICATIONS AND PRESENTATIONS

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