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Tech Social Capital in Black & Latino High School Communities: A Growing Aspect of Computer Science Education and Workforce Development

Author
Madda, Mary Jo

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Tech Social Capital in Black & Latino High School Communities:

A Growing Aspect of Computer Science Education and Workforce Development

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by

Mary Josephina Madda

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ABSTRACT OF THE DISSERTATION

Tech Social Capital in Black & Latino High School Communities:

A Growing Aspect of Computer Science Education and Workforce Development

by

Mary Josephina Madda

Doctor of Education

University of California, Los Angeles, 2023

Professor Kristen Rohanna, Co-Chair

Professor Linda Sax, Co-Chair

This dissertation aimed to address existing research gaps in the understanding of "tech social capital" amongst Black and Latino/Hispanic high school students in afterschool computer science education programs. The research employed an exploratory mixed methods approach, with afterschool high school coding program Code Next as its sample site. Given the lack of social capital measurement instruments in education, this study analyzed a set of interviews regarding students' understanding of their networks and access to resources, and used that information to adapt (and then run) an existing social capital instrument from the public health sector.

Five findings from this study demonstrated the presence and importance of tech social capital networks in Black and Latino/Hispanic high school students' lives. First, students reported having at least one significant relationship that encouraged their interest in and exploration of computer science. Second, almost every student reported that relationships contributed computer science-related resources to their lives, with adult-student relationships contributing at least two resources and peer-peer relationships contributing at least one resource. Third, students expressed that these relationships had a largely positive impact on their interests in and around computer science. Fourth, Black and Latino/Hispanic high school students perceived an increase in their tech social capital through their program participation. Fifth, student perceptions of social capital change suggest the multiplicative nature of relationships, in that a single relationship can lead to acquisition of multiple resources.

Across these findings, four themes emerged—1) afterschool programs can provide significant tech social capital in the form of institutional agents and hardware access, 2) Black and Latino/Hispanic students enter these spaces already possessing some tech social capital, 3) there are differences between live and online learning environments, e.g., sustained access to physical hardware, and 4) there is utility in quantifying tech social capital for education practitioners, researchers, and corporate technical organizations.

The dissertation of Mary Josephina Madda is approved.

José-Felipe Martínez

Jean Ryoo

Karen Brennan

Linda Sax, Committee Co-Chair

Kristen Rohanna, Committee Co-Chair

University of California, Los Angeles

2023

To Wendy, Hezekiah, Brielle, Naia, Gideon, Hibah, Ashley, and every single one of my past and current students.

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I will forever hold you in my heart.

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Vita

EDUCATION

2013	M.Ed. Technology, Innovation & Education Harvard University Cambridge, Massachusetts
2009	B.A. Art Theory & Practice / Art History Northwestern University Evanston, Illinois

WORK EXPERIENCE

2017-Present	Senior Program Manager, Education for Social Impact Google Mountain View, California / Los Angeles, California
2013-2017	Senior Editor & Director of Audience Development EdSurge Burlingame, California
2012-2013	Online Education Instructional Designer and Developer Scratch / MIT Media Lab Cambridge, Massachusetts
2011-2012	Director of Curriculum, Math Teacher St. Cyril of Jerusalem School Encino, California
2009-2011	Sixth Grade Level Chair and Science Teacher KIPP / Teach For America Houston, Texas

PUBLICATIONS

Alvarez, A., Burge, L., Emanuel, S., Gates, A., Goldman, S., Griffin, J., Madda, MJ & Washington, G. (2020). Google tech exchange: an industry-academic partnership that prepares black and latinx undergraduates for high-tech careers. *Journal of Computing Sciences in Colleges*, *35*(10), 46-52.

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AWARDS

2016	Forbes 30 Under 30, Education Forbes

Chapter 1: Introduction

As the world becomes increasingly digital and technical automation renders certain jobs obsolete, computer science education can prepare K-12 students for the developing workforce. However, while most computer science education focuses on hard skill development (Fisher, 2018; Margolis et al., 2018; Davis et al., 2021), *social capital*—one of the most crucial tools for succeeding in the working world—receives insufficient attention, despite ample evidence that social capital development contributes to an individual's networks and subsequent confidence building, self-actualization, and knowledge attainment (Lancee, 2012; Piracha et al., 2016; Bucholtz, 2019).

Computer science education spaces can be a fruitful environment for social capital development. While formal computing education spaces fall short due to policy limitations and racial underrepresentation in coding classes (Ericson, 2016; Margolis et al., 2018; Davis et al., 2021), afterschool coding programs—a tenet of the informal learning space—have emerged over the course of the 21st century in both live and online formats (Rogoff et al., 2016; Roberts et al., 2018). Researchers often identify these programs as an effective solution for preparing Black and Latino/Hispanic students for roles in cybersecurity, cloud computing and e-commerce—three of the fastest growing digital job markets (Kafai et al., 2009; Jin et al., 2018).

However, few research studies have attempted to 1) explore the impact of afterschool coding programs on social capital development, or 2) describe how afterschool programming might build upon a student's existing capital. Despite the ever-expanding technical job market (OECD, 2001a), there is a dearth of research addressing how students develop social capital connecting them to the technical and computer science career fields. Furthermore, social capital studies seldom incorporate student voice into the development of qualitative interview questions or measurement instruments. Thus, this research examines how Black and Latino/Hispanic high school students' "tech social capital" develops over the course of involvement in an afterschool computing program.

Statement of the Problem

Background of the Problem

Computer science has consistently topped the list of economists' most rapidly growing job sectors. Every few years, the World Economic Forum publishes its "Future of Jobs" Report (World Economic Forum, 2023), and in the most recent studies, jobs in cloud computing, big data, and artificial intelligence moved up the list in increasing demand from employers (2016, 2020; 2023). With tens of thousands of STEM (science, technology, engineering, and mathematics) introduced into the world every year (Bureau of Labor Statistics, 2021), computer science education has the potential to be the great "equalizer"—the answer to issues of specialized job growth, automation, and underrepresentation in the technical workforce.

This increased reliance on computer science coincides with a lack of diverse representation across multiple racial/ethnic groups in the STEM workforce. A 2015 article in the Verge, for example, detailed that Black women only make up between 0 to 7% of the staff at the eight U.S. largest technology firms (Ricker, 2015). And this issue begins long before people enter the job market; K-16 students of color—specifically U.S. Black and Latino/Hispanic high school students—are consistently underrepresented amongst computer science education courses, nationwide Advanced Placement (A.P.) exams, and higher education majors (Margolis et al., 2018). In fact, recent research chronicled in a 2021 Code.org study found that while 51% of all U.S. high schools now offer foundational computer science courses, disparities still run rampant; Latino/Hispanic students are 1.4 times less likely than their white/Asian peers to enroll in those courses (Code.org, 2021).

Over the years, researchers have suggested that one major factor contributing to representation in the tech space relates to an individual's social capital, typically defined as an individual's network of human beings (e.g. friends, colleagues, and family members) and the acquisition of those networks in order to further potential and achieve one's goals (Bourdieu, 1986; Glaeser, 2001; OECD, 2001b; Fisher, 2018). Social capital development affects how different demographics of students traverse across their high school years, through higher education, and out into the working world (Pickering, 2011; Martin et al., 2013; Saw, 2020). In order to succeed in the technical working world, students need to develop their "tech social capital"—those networks and resources that enable an individual to access and move through computer science majors and technical careers—from an early age.

While K-12 education could be the space to develop students' tech social capital and connections to computer science experts and fields in the service of developing relevant computer science skills, the United States formal education system is grossly undersupplied and under-resourced. K-12 schools operate under a number of government-mandated requirements, most of which do not include computer science as a required subject area (Margolis et al., 2018; Code.org, 2021). Mandates tied to funding and high-stakes testing in core subject areas like math and language arts result in fewer opportunities for mentor-mentee relationship development, work-study and apprenticeship programs, and other social capital growth tactics (Wagner & Dintersmith, 2015).

There is, however, hope and opportunity. In the more recent decades, researchers have noticed an increase in computer science programming amongst informal spaces—primarily in afterschool settings—where there are fewer regulations and greater flexibility to target specific racial and socioeconomic student groups (Rodrigues, 2009; Wagner & Dintersmith, 2015; Nandi & Mandernach, 2016). Informal programs like Computer Clubhouses (Kafai et al., 2009) and summer camps like GenCyber (Jin et al., 2018) have emerged across the United States, and researchers have studied the range of positive impacts these programs have on students of color, from their self-efficacy to their increased interest in computer science (Kafai et al., 2009; Jin, et al., 2018; Braswell et al., 2021).

With the growth of these informal learning spaces has come a renewed approach to social capital development tactics (Gee et al., 2017; Fisher, 2018). More specifically, since the early 2000s, more studies have emerged targeting models for Black and Latino/Hispanic high school-aged students (Means et al., 2018). However, the field is understudied, including how deficit-oriented mindsets play into social capital metrics (Harper, 2010). These gaps require further research.

Existing Gaps in Research

While a wealth of research explores the impact of STEM programming on students' interests, only some studies target high school-level computer science education, and even fewer examine combinations of instructional delivery models. At the same time, researchers are integrating social capital theory to understand how students form networks in college and beyond—including networks in technical fields of work. However, fewer social capital studies target younger grade levels, nor do they explore how non-traditional experiences like afterschool computer science education programs can affect student social capital development. Even further, few researchers incorporate student voices or perspectives on social capital into studies.

Thus, this dissertation examines afterschool STEM education implementation through the lens of social capital theory and specifically addresses the three following gaps in research.

First, few empirical studies focus on the U.S. Black and Latino/Hispanic high school students' social capital. When studies do focus on social capital, they tend to focus on more general school programming without a racial lens (Tomai et al., 2010). When they do take a racial lens, the research targets college students progressing through higher education (Thiry & Laursen, 2011; Stolle-McAllister, 2011). And while some research shows how informal STEM "afterschool" spaces create and/or disrupt social capital formation in service of student success and mobility (Gee et al., 2017; Fisher, 2018), they do not target computer science (Ricker, 2015; Bureau of Labor Statistics, 2021).

Second, when researchers discuss social capital in communities of color, they fail to incorporate student voice into defining what "social capital" means, and deficit mindsets tend to surface—contrary to the tenets of community cultural wealth theory (Yosso, 2005; Harper, 2010; Puccia et al., 2021). Few studies apply community cultural wealth theory to their analyses, failing to acknowledge that students of color possess inherent cultural and social wealth, and that their perceptions of social capital may differ from that of the research community.

Lastly, few education studies utilize an index of social capital measurement to study both live and online models of social capital development. Oftentimes, researchers address live programs and target more qualitative measures of a student's attitudes towards self-efficacy (Saw et al., 2019), confidence in computing ability (Braswell et al., 2021), or perception of STEM fields and/or majors (Roberts et al., 2018). Meanwhile, online studies revolve around measures of digital social networks (Ellison et al., 2007; Greenhow & Burton, 2011; Kasperski & Blau, 2020), rather than online instructional computing programs. Given the recent rapid shift from live to online instruction due to COVID-19, there is significant opportunity to study live and online programs in tandem, utilizing a common index as measurement.

Introduction to Study

Goals, Research Questions and Methodology

Given these gaps, I employed a mixed methods design to answer the following research questions:

1. How do Black and Latino/Hispanic high school students describe the network of relationships in their lives?
    a. How do Black and Latino/Hispanic high school students describe the impact of those relationships on their thoughts around computer science?
2. To what extent do Black and Latino/Hispanic high school students perceive a change in their tech social capital during an informal, afterschool computer science program?
    a. Does the extent of perceived change differ between participants who participated in-person vs. online?

Utilizing an exploratory sequential mixed method design, I first ran qualitative interviews with Black and Latino/Hispanic students engaged in an afterschool computer science education program. Questions addressed how students understand the network of relationships in their lives as it supports their engagement with computer science. Upon analysis of the interviews, I utilized learnings to adapt an existing social capital survey in creation of a new "Personal Tech Social Capital" survey. I then ran that survey with a larger group of participants, who answered questions regarding both the time before they joined the afterschool program and their current point in the program. Since some of the participants attend the in-person version of the program while others participate in an online version, I segregated and compared survey data between those two groups as the final step.

Researchers debate how to measure social capital. Woolcock and Jones (2007) suggest fusing qualitative and quantitative means to capture the "multi-dimensional" nature of the topic, and provide "a more comprehensive picture of the structures, perceptions and processes of social capital" (p. 398). As Creswell & Creswell (2018) describe, at a procedural level, mixed methods research studies are useful for developing a "more complete understanding of changes needed for a marginalized group" (p. 216). The use of a mixed methods approach provided the opportunity to study social capital development from multiple angles—from the perspectives of the Black and Latino/Hispanic students involved, and from a quantitative measurement perspective.

Study Significance

Students continue to age in an increasingly technical working world that breeds new industries every day, from cloud computing to data analytics to "the Internet of Things." Yet, that growth raises further issues of tech representation and "technological unemployment" (Peters, 2017). Learning how to code no longer suffices as the sole mechanism for continual tech workforce adaptation. As Bourdieu described in 1986, social capital can both further an individual's success in education and career, and be convertible to economic capital under the right conditions. Thus, educators and learning environments—whether informal or formal—possess a duty to students to develop and measure their tech social capital as intently as hard computer science skills. This study will explore ways to develop and track changes in tech social capital, ultimately producing a survey instrument that can ideally be adapted by both informal and formal high school education spaces alike. Additionally, the study will avoid a deficit model by incorporating the voices of students of color when discussing perceptions of social capital development, henceforth setting an example for future social capital researchers.

Chapter 2: Literature Review

Workforce development requires constant adaptation. The rise of the digital world means learning environments must adapt and better develop students' social capital networks. Although researchers do address computer science education in K-12 learning environments, few studies delve into social capital development for students of color within organizations where students interact with peers and non-familial adults. Additionally, the dearth of research is even more pronounced when it applies to potential success in computer science majors and careers, and few studies recognize their own deficits in bias and methodology.

In the following literature synthesis, I first define "social capital," paying particular attention to "relational" social capital. Following, I explore how individuals develop capital, followed by a brief review of how social capital development is often researched. I then describe the current state of computer science education in K-12, identifying the unique differences between formal and informal environments. Because this study focuses on informal learning environments, I analyze empirical studies detailing current computer science education models in informal K-12 education systems. I then narrow to programs that target social capital development for Black and Latino/Hispanic high school students. Subsequent analysis of these studies reveals a dearth of community cultural wealth theory and social capital measurements. I conclude with a summary of the literature and relevance to my study.

The Role of Social Capital

When it comes to acquiring jobs, prospective employees—especially in the technical workforce—not only have to be mindful of their skill sets, but also their *social capital*. In 1916, writer and educator Lyda Hanifan coined the term "social capital," later going on to specifically define it in 1920 as "those tangible assets [that] count for most in the daily lives of people" (p.

102). But French sociologist Pierre Bourdieu is oftentimes cited as the father of "social capital theory;" in 1986, his seminal work defined the phrase as "the aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance or recognition" (Bourdieu, 1986, p. 248). Bourdieu described that social capital can be broken down into 1) the relationships themselves affording resources, and 2) the quality and amount of those resources, and that social capital is convertible to economic capital under certain conditions.

Researchers have further refined that definition to describe an individual's network of human beings (e.g., friends, colleagues, and family members); the acquisition of those networks furthers one's potential and achievement of goals, whether academic or career-related in nature (Glaeser, 2001; OECD, 2001b; Fisher, 2018). Studies have demonstrated the impact of social capital on everything from college progression and retention to finding jobs post-degree completion, regardless of an individual's skill set (Seibert et al., 2001; Choy, 2002; Kang et al., 2015). Any improvements in social capital, which this study seeks to understand, will likely enhance their job prospects.

Various researchers suggest that there are three dimensions of social capital, and that their different components interrelate (Tsai & Ghoshal, 1998; Bond III et al., 2008). *Structural social capital* is rooted in structured environments—ties established between individuals and the activities that bind them together within societal structures, such as attending the same school or working at the same job. Researchers describe that when "institutions" have these ties, the individuals involved are more likely to exchange resources than go outside of the network; some researchers, in fact, refer to structural interchangeably as "institutional" social capital (Putnam, 1993; Völker & Flap, 1995; Krishna, 2000; Veenstra, 2002). *Cognitive social capital* refers to the attitudes and values that contribute to the willingness of individuals to share resources, with "trust" and "solidarity" being the most frequently-referenced value. Oftentimes, a coded language bonds these individuals together, such as common vocabulary, jokes, and/or jargon (Putnam 1993; Fukuyama 1995; Coleman 1990; Gambetta 1988; Portes & Sensenbrenner 1993).

Most recently, *relational social capital* has emerged as a third type, more deeply diving into the nature and quality of relationships. Relational hones in on individual relationships, rather than the larger shared societal bonds of cognitive social capital; a relationship between a student and a mentor, for example, fits into the category of relational social capital (Claridge, 2018). In this study's case, the methodology and analysis seeks to analyze that third component—relational social capital, or how students develop relationships with both their peers and adults. *Bonding* and *bridging* are the two common descriptors for social capital—the first describing "strong" ties between individuals who are alike, and the second describing "weaker" ties between people who are different (Claridge, 2018). Bonding social capital tends to describe ties between individuals of similar background, interest, ethnic groups, demographics, and/or social class (Putnam, 2000), while bridging connects individuals across those groups, though less rooted in bonding values like trust and commonality. A third type of relational capital, introduced in the early 2010s, is *linking* social capital, in which individuals build relationships with various institutions and persons with power and influence (Hawkins & Maurer, 2010; Poortinga, 2012). For the sake of this study, the methodology will target relational capital, which will be further broken down into bridging, bonding, and linking social capital as topics of analysis.

How Social Capital Develops

Researchers provide varied explanations as to how one gathers social capital, though many tend to identify networks and human interaction as crucial to the development of social capital, coupled with interpersonal trust, shared values and norms (Fisher, 2018; Glaeser, 2001; OECD, 2001b). In the education space, studies document how individual educational institutions and programs provide space for those networks (structural social capital), relationships (relational social capital), and trust (cognitive capital) to grow (Frank et al., 2008; Pickering, 2011; Saw, 2020). An Adolescent Health and Academic Achievement Study (AHAA) examined the development of same-sex academic networks and its impact on female high school students as an example of structural social capital, where female students are more likely to take advanced courses when surrounded by other female peers with higher level math coursework experience (Frank et al., 2008). Other studies describe the development of both relational and cognitive social capital through mentorship programs, looking at institutions that place emphasis on providing ample time for student interactions with mentors in relevant career/college major fields (Hunter et al., 2009; Thiry & Laursen, 2011; Rodriguez et al., 2023).

Social capital theory implies that those with more, larger and stronger networks, relationships, and interpersonal trust excel at achieving their goals through resources made available by connections, or "resources that can be accessed or mobilized through ties in the networks" (Bucholtz, 2019, p. 3). Earlier in the 2000s, the Organization for Economic Co-operation and Development (OECD) described social capital as a space requiring further investigation (OECD, 2001a) in regards to student pursuit of higher education and career progression. As of the 2010s, more and more scholars tie the importance of social capital to improving labor market outcomes, arguing for increased focus on the relationship between "social relations" and "finding a job" (Lancee, 2012; Piracha, et al. 2016, Faucher, 2018). Both Lancee and Piracha et al. used longitudinal survey data from the Netherlands and Australia, respectively, to demonstrate the positive impact of immigrants' social networks on their ability to secure a job in new countries, especially for women.

The Utility of "Tech Social Capital"

Social capital can be utilized both by existing powers to retain that power, à la an "old boys network" (Putnam, 2000), and by individuals seeking to progress and diversify homogeneous spaces. Thus, this study plans to explore social capital development amongst high school students of color, but specifically as it applies to the "tech" space. Racially-diverse representation in the STEM workforce is paltry, to say the least. Although Black workers account for about 12% of the U.S. workforce, they make up only 6% of software and web developers; Latino/Hispanic workers represent just 5% of software and web developers, even though they are 18% of the total U.S. workforce. When accounting for intersectional data like the gender-race crossover, the stats highlight even greater disparities (Bureau of Labor Statistics, 2021). As such, this study seeks to understand how the development of *tech social capital*, or relational social capital benefiting an individual in the tech world, can start from a young age.

There is great potential in this space, given that researchers in other sectors (including economics, public health and sociology) have explored similar theories and found that social capital can improve with more than just access to higher education and job opportunities. An analysis of the National Longitudinal Survey of Youth, for example, found that young adults who found jobs through informal networks had higher wages relative to those who used more formal job searching and application techniques (Kramarz & Skans, 2014; McDonald 2015). However, the issues begin far before adults enter the workforce, which argues for K-12 interventions, like the one proposed in this dissertation.

Family and Neighborhoods vs. Education Organizations

For any student, social capital development takes place across a multitude of locations. However, education scholars at the Search Institute conducted a recent review of adolescent social capital literature (2020), ultimately finding that most studies tend to focus on parent and neighborhood relationships. According to the review, academics pay considerably less attention to studying social capital stemming from relationships with peers and adults in organizations and programs serving YYAs (youth and young adults) of color and from low-income backgrounds. Those organizations include schools, congregations, mentoring programs, and work organizations, to name a few. Many other scholars have also noted this (Dika & Singh, 2002; Al-Fadhli & Kerson, 2010; Rothon et al., 2012; Booth & Shaw, 2020; Rodriguez et al., 2023), reporting patterns of family social capital measures.

Aware of this reality, scholars like Stanton-Salazar (2011) have called for more exploration of social capital within organizations serving YYAs external from the home or neighborhood environments. These organizations often have what Stanton-Salazar calls "institutional agents," or individuals positioned to broker learning opportunities, connections to institutions, and/or access to resources that can help students navigate different environments and reach their goals. In fact, Stanton-Salazar created his own institutional agents social capital (IASC) framework to explain how institutional agents can either facilitate or hinder students' access to social capital.

K-16 Computer Science Education in Tech Social Capital Formation

For many students, social capital development takes place in schools—and one way to reduce disparities in technical fields is to improve computer science education programming in K-16 education. Here, students could develop their tech social capital from an early age. However, unlike other traditional STEM offerings like biology and mathematics, K-12 computer science is not considered a core subject (Nager & Atkinson, 2016). Only 47% of schools in the United States actually offer computer science courses (Margolis et al., 2018; Davis, et al., 2021). When K-12 programs do offer computer science courses to students, racial and gender disparities quickly emerge. For example, Barb Ericson's (2016) review of the 2016 A.P. Computer Science A course exam revealed that only 9.2% of test-takers are Latino/Hispanic and 3.8 are were Black—despite the fact that the total number of total test-takers had a 17.3% increase over the previous year.

Since the early 2000s, informal learning research has increased in both quantity and scope as the number of computer science informal learning environments has grown in number and breadth. Scholars have attempted to define the space according to its lack of formalized assessments, and oftentimes voluntary and varied settings (Rogoff et al., 2016; Roberts et al., 2018). Computer science-related informal learning research includes studies of nonprofit-led afterschool computing programs (Kafai et al., 2009; Braswell, et al., 2021), summer camps (Jin et al., 2018), and higher education programming like hackathons (Wagner & Dintersmith, 2015; Nandi & Mandernach, 2016).

Informal learning environments have advantages in that they retain fewer limitations in what and when to teach and assess (Rodrigues, 2009; Roberts et al., 2018). Thus, they can address the issue of preparing high schoolers of color for the future computational workforce more flexibly. Informal programs like Computer Clubhouses (Kafai et al., 2009) and summer camps like GenCyber (Jin et al., 2018) design their programs around problem-based project work, teach content more specific than "computer science," and create non-punitive and non-high stakes formats of assessment to track student progress.

When isolating the impact for Black and Latino/Hispanic students, the results appear mostly positive in increasing students' feelings of self-efficacy and interest in computer science (Kafai et al., 2009; Jin et al., 2018; Braswell et al., 2021). For example, researchers analyzed the efficacy of GenCyber summer camp to introduce relevant job skills like cybersecurity concepts to 181 Indiana-based high school students with a 51.3% underrepresented minority ratio. The study included a 1-to-5 survey scale measuring satisfactory rate of camp activities and feelings of self-efficacy, ranging from 5 (strongly agree) to 1 (strongly disagree), where non-Caucasian students scored an average of 4.07 (Jin et al., 2018).

Live programs are far from the only space that informal computer science education enthusiasts have touched. Online programs have developed in their own right, including self-paced curriculum like Code.org, massive online courses (MOOCs) and virtual, teacher-taught courses (Aspray, 2016; Grella et al., 2016). Along the way, researchers have advocated for further study of the overall impact of online programs on high school students (Anohah, 2016). This study targets an informal afterschool program focused on Black and Latino/Hispanic students—and one that considers both live and online versions. Findings will provide opportunities for development and further study.

The Role of Afterschool Coding Programs

With flexible programming, informal STEM "afterschool" spaces allow for social capital formation where formal spaces fall short. Since the early 2000s, research shows how these spaces create and/or disrupt social capital formation in service of student success and mobility (Gee et al., 2017; Fisher, 2018; Puccia et al., 2021). Specifically, the studies unveil how students not only develop social capital, but also retain, strengthen and multiply that capital throughout school years and into post-secondary years. Such retention enables enduring connections outside of students' immediate communities. Other organizations have described the role of education institutions as "meeting places" where different social networks can intersect, as schools can provide breeding grounds for ideas, discussions, and cultural diversity between these different networks (OECD, 2001b). Pickering's four-month qualitative study of the singular Dublin, Ireland Computer Clubhouse (2011) chronicles her experience observing and interviewing Clubhouse staff, partners and members (including the CEO, long-term volunteers, and a principal). She concluded that the Clubhouse does play a role in introducing students to different knowledge economies and helping students to understand technical career pathways and the certifications required to pursue those pathways. This study built on an already existing study of the larger Computer Clubhouse network, which SRI International found improved students' feelings of belonging and self-efficacy (Michalchik et al., 2008).

Early 2000s studies of capital formation in afterschool coding programs were not without limitations. However, they set examples for later studies in the 2010s to expand reach and increase participant numbers. This expansion was particularly significant as researchers began to target social capital development models for Black and Latino/Hispanic high school-aged students in both in-school and afterschool programming. A 2018 study of a formal education program, for example, reviewed a total of 23 inclusive STEM high schools and 19 comparison schools without a STEM focus. Results demonstrated that students from underrepresented groups who had attended STEM-focused, structural social capital-heavy high schools were significantly more likely to be in a STEM bachelor's degree program an entire two years after high school graduation (Means et al., 2018).

Meanwhile, studies of informal learning programs have widened to include nonprofit programs like Brother2Brother, government initiatives like My Brother's Keeper (Zell, 2011), and university programs like the University of Texas at San Antonio's PREP program, which was found to have little or no differential effects on students' attitudes towards STEM careers across gender, racial/ethnic, or socioeconomic groups (Saw et al., 2019). Inspired by these more recent studies, my own research builds on existing research by taking a more targeted approach. Namely, this study focuses on one facet of social capital—relational—instead of generalizing the social capital concept or attempting to demonstrate a causal relationship between social capital and attitudes towards STEM.

Online vs. Live Programming for Capital Formation

In-person afterschool programs are not the only format for social capital formation—quite the contrary. With the rise of the internet and networking sites, online informal models and "online social capital" have received more study since the mid-2000s. Research tends to target social networking websites (e.g., LinkedIn, Twitter, Facebook), examining the impact of website participation on student-student relationships (Ellison et al., 2007; Greenhow & Burton, 2011) and student-teacher relationships (Kasperski & Blau, 2020). Few studies, however, examine how online learning programs affect K-12 students' networks.

More recent studies pertain to Black and Latino/Hispanic students' digital social networks, indicating an increasing interest in the potential for social capital development online. Greenhow & Burton (2011), for example, surveyed responses from 607 high school students from low-income families and found results suggesting positive associations, particularly for Latino/Hispanic students, between student use of online social network sites and their bridging/bonding relational capital. Other studies explore more structured digital networks, like university-run online mentoring programs or nonprofits like iMentor, with varying degrees of success across their impact on structural, relational and/or cognitive capital (Merrill et al., 2017; Garcia-Melgar & Meyers 2020).

However, few studies draw a direct comparison between online and live programs for social capital development, instead showing how online social capital formation affects student performance in live programming, predominantly at the higher education level (Kent et al., 2019; Salimi et al., 2022). Others simply acknowledge the need for more studies comparing live and online learning experiences (Williams, 2017). Given the vast number of afterschool programs that moved to online settings because of the COVID-19 pandemic, this study seeks to address whether a program's live and online versions yield comparable outcomes in student social capital development.

The "Community Cultural Wealth" Factor, Deficit Mindsets, and Student Voice

While there is no shortage of research on informal learning environments, many of the aforementioned studies fail in the eyes of *community cultural wealth theory*—a theoretical framework challenging social capital theorists' deficit mindsets. Rooted in 1970s and 1980s critical race work from the likes of Derrick Bell, Alan Freeman and Kimberlé Crenshaw (Bell, 1975; Freeman, 1977; Crenshaw, 1988), community cultural wealth theory entered into the lexicon when researcher Tara J. Yosso published her seminal 2005 "Race, Ethnicity, and Education" article. Yosso recalls one of critical race theory's core principles as the recognition of "deficit thinking"—a common mindset that minority students and families possess little to no cultural knowledge, skills, or networks when entering into educational institutions (Yosso, 2005). Her article built off of other scholars' earlier research (Delgado Bernal, 1998; Ladson-Billings, 2000) and challenged supposedly "neutral" research as a mere mechanism for distorting Black and brown communities' epistemologies.

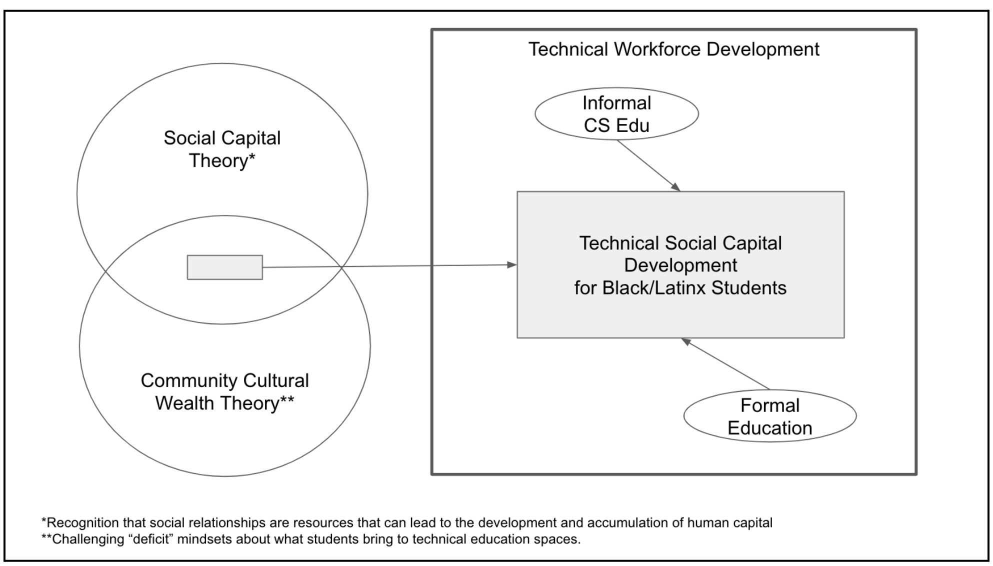
In the article, Yosso introduced “community cultural capital” as a means of describing the capital that students bring to the table—including social capital—when they enter new spaces. Another term coined and further described by Pierre Bourdieu (Bourdieu & Passeron, 1977), *cultural capital* describes a person’s skills, assets and resources. As Yosso describes, cultural capital has been used to assert that some individuals, often described by particular racial demographics, are inherently “wealthy” while others lack cultural capital (Yosso, 2005). Yosso sets up her own concept of “community cultural wealth” as a combination of aspirational, navigational, linguistic, familial, resistant and finally, social capital—“not mutually exclusive or static,” but building on one another. As such, Yosso’s attempt to rethink cultural capital from a non-deficit lens highlights a lack in the field of K-12 social capital research focused on students of color.

When reviewing the literature, few studies of social capital development in high school informal learning environments prove self-aware of a deficit mindset. In fact, most refrain from applying the tenets of community wealth theory to their analyses. However, college undergraduate and graduate level research differs. Researchers reference Yosso’s work in studies of Black and Latino/Hispanic STEM majors, using community cultural wealth as a lens when studying college persistence and self-identity formation (Espino, 2014; Samuelson & Litzler, 2015; Rincón & Rodriguez, 2021). This is particularly due to Shaun Harper’s research, in which he warns against spreading deficit-oriented narratives for “racially marginalized” students in STEM majors (2010).

Additionally, few high school studies incorporate student voice in the exploration of defining social capital, further adding to the deficit lens. While some include qualitative interviews with students or student advisory groups from both formal and non-formal environments alike (Jarrett et al., 2005; Greenhow & Burton, 2011; Schwartz, et al., 2018), these studies typically refrain from incorporating student perspectives into defining or quantifying social capital as students see it, in favor of fitting student perspectives into predefined descriptions or frameworks. This is a key miss.

More recent studies of the high school level acknowledging the deficit lens do exist, but tend to focus on formal environments (Rocha et al., 2022). As such, this study will examine social capital through a community cultural wealth lens as an overall orienting lens for research questions (Creswell & Creswell, 2018), and include a methodological approach that fundamentally incorporates student voice and perception. This framework is described in Figure 2.1 below.

Figure 2.1
Social capital theory x community cultural wealth theory framework



Materializing—and Measuring—Students' Tech Social Capital

An additional issue that causes major debate in the slow but steady increase of K-12 social capital research relates to measurement. In the education arena, there does not appear to be any formal consensus around a common measure of social capital (Jackson, 2019; Scales et al., 2020). Many studies vary in how they measure social capital, but some refrain from identifying a social capital index at all in favor of drawing loose connections and/or correlations between the existence of social capital and outcomes like college persistence, lower dropout rates, and increasing interest in subjects like computer science (Farmer-Hinton, 2008; Greenhow & Burton, 2011; Saw et al., 2019; Saw, 2020). Vynke and colleagues (2013) call this out directly, saying that there is a "lack of clarity on how to measure the concept and in the variety of constructs" (p. 4) regarding adolescent social capital.

By contrast, certain industries—namely health, sociology, and economics—have set the tone for utilizing social capital indices on both macro (group/community) and micro (individual) scales. Because social capital is multi-dimensional, rather than a singular entity (Grootaert et al., 2004), researchers have produced and utilized multiple quantitative and qualitative indices for measuring an individual's capital. Putnam's Social Capital Index (2000), one of the most commonly documented indices, is a 14-variable index that covers five key indicators of social capital—volunteerism, social trust, informal sociability, engagement in public affairs, and community and organizational life. Others, including Cohen's Social Network Index (1997), focus on network size, the various social roles with whom an individual has frequent contact (e.g., teacher, parent, friend) and network domains (e.g., school, church, afterschool sports).

It should be noted that these indices provide inspiration for the K-12 space, but by no means are comprehensive, directly applicable to youths, or fully reliable. For example, a research synthesis conducted by De Silva, McKenzie, Harpham, and Huttly (2005) on youth mental illness and social capital research found that many of these studies vary in methodology and outcomes, thus making them hard to summarize or pull best practices from. Other research syntheses argue similarly, instead proposing that elements of multiple instruments be blended together so as to fully test and understand impact (Dika & Singh, 2002; Scales et al., 2020).

The Search Institute, funded by the Bill and Melinda Gates Foundation, more recently identified and created commonly-used tools for measuring social capital (name generators and position/resources generators) as well as technology-enhanced methods for collecting live and digital social capital data (2020). Name generators, often acquired through interviews or surveys, target the numbers and types of relationships young people have (Burt, 1984; Burt et al., 2012; Ashida, Wilkinson, & Koehly, 2010; Creswick et al., 2009). Position generators target the variety of roles and prestige of those roles held by an individual's network contacts (Lin & Erickson, 2008). "Resource generator" is an alternative term for this concept in that it seeks to better understand the resources afforded to an individual through contacts, rather than those contacts' positions (Van der Gaag, 2008). The Search Institute also moved one step further and released its own collection of Social Capital Assessment + Learning for Equity (SCALE) Measures, in the form of survey questions and qualitative assessment (Search Institute, 2021). A few organizations and research groups have since adapted these measures how they see fit, though the measures have not yet been independently validated.

Additionally, novel quantitative methods of assessing online social capital have emerged in congruence with the rise of the internet, including social network analysis (Abbasi et al., 2014), a quantitative method used for assessing relationships and links between different individuals and/or groups. The Harvard Opportunity Insights organization, for example, adapted elements of the SCALE Measures (Chetty et al., 2022) to create the "Social Capital Atlas," an open-access tool that analyzes Facebook relationships to explore "economic connectedness," a theoretical predictor of economic mobility.

Prior to embarking on any new social capital research, scholars first recommend identifying what capital to measure—structural, relational, cognitive—and subsequently identifying the appropriate indices and indicators for use (Dika & Singh, 2002; Scales et al., 2020). This can become increasingly complex when breaking down topics further; relational capital, for example, can be broken into strong "bonding" ties and weaker "bridging" ties (Poortinga, 2012; Lancee, 2012). Some non-education scholars have addressed this; Chen's 2009 "Personal Social Capital Scale" contains items assessing indicators of bridging, bonding and linking social capital, as does Cohen's "Social Network Index" (1997). Nonetheless, the call for clarifying social capital metrics in education research is clear.

A small number of education researchers have attempted to measure relational social capital, albeit without "bridging," "bonding," or "linking" descriptors. Israel and Beaulieu's study of school social capital (2004) includes items like "the amount of discussion between a student and his/her teachers" (p. 42). Dufur's study measures relational school capital with students' responses to statements like "Do you feel close to people at your school?" (Dufur et al., 2015). The following methodology for this study will integrate items from both education social capital indices and indices from non-education sectors.

Chapter 3: Methodology

According to social capital theory, social capital development provides individuals with fruitful resources that contribute to higher education and career progression (Bucholtz, 2019; OECD, 2001a). Relational social capital in particular correlates with several positive postsecondary outcomes, including greater education attainment (e.g., college retention, higher GPA) and promotional opportunities (Dubois et al., 2011; Ghosh & Reio, 2013; Kim & Schneider, 2005; Stanton-Salazar, 2011). However, studies tend to focus on social capital formed within families and neighborhoods; few studies address social capital development for K-12 students within organizations, especially for students of color (Al-Fadhli & Kerson, 2010; Booth & Shaw, 2020; Dika & Singh, 2002; Rothon et al., 2012). The field becomes even narrower when targeting afterschool computer science education. The area is in need of further study, considering the importance of those environments in developing a student's tech social capital and subsequent success in an increasingly tech-based world (Kramarz & Skans, 2014; McDonald, 2015; Bureau of Labor Statistics, 2021).

Thus, this study sought to examine how Black and Latino/Hispanic high school students' relational tech social capital developed during a five-month engagement in an afterschool computing program, as well as how students describe the network of relationships and resources in their lives. I sought to answer the following research questions:

Research Questions

1. How do Black and Latino/Hispanic high school students describe the network of relationships in their lives?
    a. How do Black and Latino/Hispanic high school students describe the impact of those relationships on their thoughts around computer science?

2. To what extent do Black and Latino/Hispanic high school students perceive a change in their tech social capital during an informal, afterschool computer science program?
    a. Does the extent of perceived change differ between participants who participated in-person vs. online?

Research Design and Rationale

In order to understand students' perception of their networks and how their tech social capital changes over time, I employed a multi-step design. This design captured student reflections through interviews and I used that data to generate a survey instrument quantifying changes in capital. Thus, I utilized an exploratory sequential mixed method approach in my research.

First, I conducted 20 qualitative interviews with Black and Latino/Hispanic students enrolled in Code Next, an afterschool computer science education program. Approximately half of the students take part in the in-person version of the program, and the other group of participants in an online version. I then analyzed the interviews and used major themes to create a new survey instrument adapted from Chen et al.'s externally-validated Personal Social Capital Scale (2009). I then ran that survey with 88 participants, who answered questions regarding both their "pre-program" situation and their "current" experience in the program. Following, I conducted two statistical analyses—one where I compared the overall "pre-program" and "current" social capital scores, and one where I examined the differences in quantitative social capital changes between in-person students and online students.

Many social capital scholars tend to pursue a singularly quantitative or qualitative approach to their studies. However, Woolcock & Jones (2007) suggest fusing qualitative *and* quantitative means to capture the "multi-dimensional" nature of the topic, and provide "a more comprehensive picture of the structures, perceptions and processes of social capital." In fact, Creswell & Plano specifically address the utility of exploratory mixed method studies cases in that they are "useful when seeking to understand complex social phenomena" that are "difficult to study with a single methodological approach" (Creswell & Plano, 2011, p. 53). A mixed method descriptive approach with pre- and post-surveys provides an affirmative stance on the ability to measure social capital, falling in line with popular social capital indices in public health and sociology (Cohen, 1991; Chen et al., 2009). And by adding quantitative methods, "information can be quantified and subjected to statistical treatment in order to support or refute 'alternate knowledge claims'" (Creswell, 2003, p. 153)—in this case, the claim that social capital cannot be measured in growth.

While a singularly qualitative or quantitative approach could be applied, neither provides sufficient color or details regarding social capital changes for marginalized groups over a period of time. First, a qualitative-only design would lack a sense of statistical significance, and leaders in power at technical organizations often respond better to numerical data than qualitative-only data. This sentiment is shared by the Search Institute's 2020 review of social capital literature, which describes social capital as a "multidimensional construct" that requires "multiple methods" to fully understand (p. 47). Second, in terms of the quantitative survey methods, "information can be quantified and subjected to statistical treatment in order to support or refute 'alternate knowledge claims'" (Creswell, 2003, p. 153), and a quantitative-only design would fail to address actual reasonings or explanations on its own. Lastly, Creswell & Creswell (2018) describe that mixed methods research studies are useful for developing a "more complete understanding of changes needed for a marginalized group" (p. 216). Thus, this study uses an intervention involving complex structures to investigate the changes in social capital of Black and Latino/Hispanic high school students.

Site, Population, and Sample

This study required a site that engages Black and Latino/Hispanic high schoolers in computer science programming, specifically in the afterschool setting. The Code Next program served as the site, with Black and Latino/Hispanic high school students (grades 9-12) as the target population. Code Next is a computer science afterschool program funded by Google that provides students with direct contact to 1) computer engineers and coders, who serve as coaches, and 2) other Black and Latino/Hispanic students with interests in computer science and the technical fields.

The Code Next program has both a "Live" program with physical labs in three cities (New York, NY; Oakland, CA; Detroit, MI) and a comparable online version (called "Connect"). Many of the in-person and online students' communities lack afterschool coding programs designed specifically by and for people of color, thus validating the importance and application of this study. The Code Next site locations have an average demographic breakdown of ~52% Black and ~38% Latino/Hispanic (~10% as a mix of Native, Asian, White, or Other). Many states, including Michigan and California, have no statewide computer science requirement, and New York does not require any computer science courses for a student to graduate from high school. For the online program, Code Next Connect is ~60% Black and ~30% Latino/Hispanic. There has been some research in the area of social capital when it comes to online-only learning communities (Williams, 2006; Tomai et al., 2010; Karnick, 2011; Greenhow & Burton, 2011). However, few of those experiments focus on live programming adapted for an online environment. Given the COVID-19 pandemic and the acceleration of live-to-online adaptation, the opportunity to compare online-only and live-only programming during the early 2020s was ripe for study.

Rationale for Sample Selection

My study focused on Black and Latino/Hispanic students who participated in Code Next live labs and online afterschool clubs during the Fall 2022 and Winter 2023 semesters, as Code Next runs similar clubs in the lab and the online program. Google coaches (current software engineers who coach part-time and full-time lab staff) served as the coaches for these clubs.

Table 3.1
Demographic characteristics of student study participants

	Interview Participants (n=20) n / %	Survey Participants (n=88) n / %
Gender		
Female	10 / 50%	33 / 37.5%
Male	9 / 45%	51 / 58.0%
Non-binary / other gender	1 / 5%	3 / 3.4%
Prefer not to say	0 / 0%	1 / 1.1%
Race/Ethnicity		
Black only	11 / 55%	54 / 61.4%
Latino/Hispanic only	8 / 40%	31 / 35.2%
Multi-racial (Black and Latino/Hispanic)	1 / 5%	3 / 3.4%
High School Grade Level		
Freshman	7 / 35%	22 / 25%
Sophomore	6 / 30%	12 / 13.6%
Junior	2 / 10%	33 / 37.5%
Senior	5 / 25%	21 / 23.9%
Program		
In-Person	9 / 45%	38 / 43.2%
● Code Next Detroit, MI	*3 / 15%*	*5 / 5.7%*
● Code Next Oakland, CA	*1 / 5%*	*15 / 17%*
● Code Next New York, NY	*5 / 25%*	*18 / 20.5%*
Online	11 / 55%	50 / 56.8%

For the first part of the study, I conducted interviews with 20 Code Next students who participated in the "live" in-person program and in the "Connect" online program. Of those students, 9 attend the in-person program (45%) and 11 attend the online program (55%). Table 3.1 summarizes some of the demographic characteristics of these students. I asked interested students to select the best dates and times that worked for them. From that group, I scheduled times with the fastest-responding Black and/or Latino/Hispanic students. There were a few exceptions to this. First, there was some lag with Detroit-based and Oakland-based students responding, so I saved a few spots for those students before filling up the 20 spots with only New York City and online "Connect" students. Second, I made sure to get close to equal representation between the "live" program and the "online" program; because online students signed up more quickly, I capped the number of Connect interviews to 11.

For the second part of the study, all active Code Next students (463 in total) received an email inviting them to participate, and 129 students responded (27.9% response rate). Of that 129 students, 68 attend the Code Next in-person program, and 61 attend the online program. I analyzed data from only those students who identified as Black and/or Latino/Hispanic. Of the 68 students who attend the in-person Code Next "Live" program, 38 identify as Black and/or Latino/Hispanic; of the 61 who attend the online program, 50 identify as Black and/or Latino/Hispanic. Again, overall demographic characteristics are summarized in Table 3.1, while differences between the online and live communities are further described in Table 3.2. It is worth noting that amongst the survey respondents, certain demographics received higher representation than others. As shown in Table 3.2, live respondents proved more evenly distributed amongst genders and races/ethnicities. Online, on the other hand, had higher female and higher Black representation overall.

The online and live Code Next communities possess several similarities and differences. Both communities feature predominantly Black and Latino/Hispanic high schoolers who are typically coding beginners. All students self-select into the program and receive all the necessary technology (including laptops and WiFi hotspots) to be able to engage in the program. All students participate in quarterly clubs that have between 10 and 15 students. Lastly, in both live and online clubs, students learn content two hours per week over a nine-week period for each club that they are enrolled in, and have optional opportunities for Office Hours (extra time with coaches). In terms of differences, the live labs only have students from a given geographic area, while the online clubs combine students from varying cities, states, and territories across singular time zones. (An "Eastern Standard Time Zone" or "EST" club, for example, may include students from states/territories as northern as Maine and as southern as Puerto Rico.) Additionally, live lab students are able to access the lab spaces whenever they want—even if they don't have a club on a given day. Online students, however, do not have that luxury; if they choose to interact on non-club days, the only options are through a Discord chatroom or email.

Table 3.2
Demographic characteristics of online and live survey participants

	Code Next "Connect" Online Participants (n=50)	Code Next "Live" In-Person Lab Participants (n=38)
	n / %	n / %
Gender		
Female	34 / 68.0%	17 / 44.7%
Male	14 / 28.0%	19 / 50.0%
Non-binary / other gender	2 / 4.0%	1 / 2.6%
Prefer not to say	0 / 0.0%	1 / 2.6%
Race/Ethnicity		
Black only	35 / 70.0%	19 / 50.0%
Latino/Hispanic only	15 / 30.0%	16 / 42.1%

Multi-racial (Black and Latino/Hispanic)	0 / 0.0%	3 / 7.9%
High School Grade Level Freshman Sophomore Junior Senior	 14 / 28.0% 6 / 12.0% 20 / 40.0% 10 / 20.0%	 8 / 21.1% 6 / 15.8% 13 / 34.2% 11 / 28.9%

I invited eligible students in the program to voluntarily participate in the interviews in exchange for monetary compensation, specifically $10 distributed through PayPal, Venmo, or CashApp, according to each student's preference. Once I created the survey instrument, I again invited students to participate in exchange for entrance into a raffle to win one of 20 $20 prizes, distributed via PayPal, Venmo, or CashApp. I opened up the survey opportunity to all Code Next students but only analyzed data from self-identified Black and Latino/Hispanic students.

Access to Site and Sample

I am one of the leads for the Code Next program and a current Google employee, so as a result, I had access to the site and sample. However, Google has legal and privacy constraints around conducting research. In order to gain access to the site, I first met with the other Code Next leads (and as well as the overall Code Next team lead and manager) to obtain approval for the study. I then shared the specifics with our department's resident researcher, Shameeka Emanuel. Finally, I met with our department's Engineering Education's Legal team to ensure that I could run the study. In all three cases, I presented the ethical implications of the study and the potential impact of the findings on Google's computer science education programs.

From a participant standpoint, all Code Next students (and their parents/guardians) have to sign waivers agreeing that they are willing to participate in studies conducted by research organizations. More specifically, the waiver reads:

> *I understand Google may engage one or more third parties to conduct research studies on academic engagement and student experience in a Google-sponsored program that is currently entitled 'Code Next' (each research study, a 'Study'). I understand that activities related to the Study may include observations, small group and one-on-one discussions led by a third party facilitator, completion of written surveys, and any other activities incidental to the foregoing (collectively, the "Study Activities") over the course of the Code Next program term. I acknowledge that my participation in the Study is voluntary and does not impact my or Minor's, as applicable, eligibility to participate in Code Next. I hereby give my consent to Google to share my name, telephone number, and email address with a third party facilitator.*

That being said, to ensure additional privacy and consent, I provided several more documents to students and families. First, I shared study information sheets (in both English and Spanish) for students and parents to read before taking part in either part of the study. Second, for any students under 18, I provided consent forms for parents to sign for students who wished to take part in the interviews and/or the surveys. Additionally, to establish further emotional trust, I reminded students throughout interviews and recruitment that 1) participation in this study is both voluntary and incentivized, and 2) that I will anonymize their answers in the final presentation.

Data Collection Methods

Interviews

First, I conducted 20 face-to-face, 1:1 interviews—nine representing the live program, and eleven representing the online program—in November and December of 2022. Again, Table

3.1 summarizes the demographic characteristics of these students. The questions for these interviews are exhibited in Appendix B.

All interviews took place virtually on Google Meets, as online Code Next students are unable to do in-person interviews. Each interview ran for approximately 45 minutes. After asking the participant's permission, I recorded each interview with a MacBook and later transcribed the interviews using a Google Drive application. I crafted the questions in order to address RQ1 and RQ1a, and identified data points relevant to updating Chen et al.'s Personal Social Capital Scale survey instrument (2009). The interview questions probed deeper into how students understand and describe their networks and access to resources, specifically targeting "relational social capital"—their close and/or casual (otherwise known as "bonding" and "bridging") adult-student and peer-peer relationships.

Student Surveys and Adaptation from Existing Survey Instrument

Following the interviews, I adapted and produced a survey with an existing "Personal Social Capital Scale" index and instrument. This index (Chen et al., 2009) measures relational capital in the public health sector. The Personal Social Capital Scale includes 42 items assessing indicators of bonding and bridging social capital. Wang et al. validated the index in 2014, reviewing several components of the Personal Social Capital Scale and finding them to be reliable, valid, and able to be used to assess personally-owned social capital.

Within Chen's scale, several questions indicate "bonding" social capital (the items related to relationships), while the others indicate "bridging" social capital (the items related to assets/resources). For the new survey, six questions were adapted to produce a means of calculating a total Personal Tech Social Capital (PTSC) index score, as seen in Appendix C. Respondents receive a Personal Tech Social Capital (PTSC) index score, which is further broken up into a “bonding” social capital score, or PTSC-Bo, and a “bridging” social capital score, or PTSC-Br. The survey adaptation includes questions labeled Bo1, Bo2, and Bo3 (for bonding questions) and questions labeled Br1, Br2, and Br3 (for bridging questions).

After coding themes during the qualitative analysis (described more in the next “Qualitative Interview Data” section), I coded to a point that matched the specifics of Chen’s question items; in this case, the set of sub-codes shown in the second column of Appendix A. Items for questions 1, 2, and 3 were adapted from sub-codes describing students’ highest-cited relationships, and items for questions 4, 5, and 6 were adapted from sub-codes describing students’ highest-cited resources. I then uploaded the survey into Qualtrics with several demographics questions attached, as seen in Appendix D.

In March 2022, Code Next staff administered the online survey via email to all 463 Code Next students who were enrolled in the winter semester of 2023. 129 students responded to this initial invitation—68 from the Code Next in-person program, and 61 from the online program. Of the students who responded to the survey, 88 students identify as either Black (61.4%) Latino/Hispanic (35.2%), or a multiracial combination of Black and Latino/Hispanic (3.4%). Out of the 88 in total, 38 attend the in-person Code Next “Live” program in one of three labs across Detroit, New York, and Oakland, and 50 attend the online Code Next “Connect” program. Demographic characteristics of the 88 student respondents are summarized in Table 3.1.

Data Analysis Methods

Qualitative Interview Data

For interviews, I engaged in a deductive, multi-step coding process in order to adapt Chen’s survey and answer my research questions.

I first used attribute coding to group respondents according to their self-identified race/ethnicity and gender, and then employed descriptive codes in order to identify generalized categories of relationships and resources. This was broken down further by additional sub-coding, followed by magnitude coding to identify frequency counts and understand students' most commonly reported answers (Maxwell, 2012; Saldaña, 2015). Appendix A shows a table that describes the overarching descriptive codes, sub-codes, and examples of each amongst the qualitative data. Amongst the description codes, six categories emerged for relationships (describing "bonding capital"), while two categories emerged for resources (describing "bridging capital"). From there, I identified sub-codes that correlated to specific items mirroring level of specificity amongst Chen's survey questions (which is further explored in Table 4.1 in Chapter 4).

For second-cycle coding, I employed pattern coding to re-review the codes and look for additional patterns related to students' relationships and thoughts around computer science. I then compared those patterns across the live and online program settings.

Quantitative Student Survey Data

Upon completing the coding process for the qualitative analysis, I adapted the Chen Personal Social Capital Scale survey instrument (Chen et al., 2009) and created a Personal Tech Social Capital (PTSC) survey instrument, presented in Appendix C.

The Personal Tech Social Capital (PTSC) index closely follows the statistical framework employed by the Personal Social Capital Scale (Chen et al., 2009). All sub-items are assessed using a four-point Likert scale with 1 = "none" or a few to 4 = "all" or a lot. Respondents received two Personal Tech Social Capital (PTSC) scores broken up into bridging (Br) and bonding (Bo) relational social capital scores. PTSC-Bo scores are calculated by (i) summarizing the individual subitem scores for questions Bo1 through Bo3 and (ii) dividing the sum score by the number of subitems. The same is true for the PTSC-Br score, though for questions Br1 through Br3. The summation of the bonding capital score and the bridging capital score yields an overall PTSC score. I further explore the role of my qualitative codes and describe the question-to-question updates to Chen's instrument in Chapter Four.

As with Chen's survey, survey respondents received overall PTSC scores by combining the cumulative total of a bonding score (PTSC-Bo) and a bridging score (PTSC-Br). However, for the PTSC survey, the questions are all asked twice—first with "before you started in Code Next," and then a second time with "currently." As such, respondents received a PTSC score for the first section of questions, as well as a PTSC score for the second section. This approach allowed for comparison of the two scores to understand how students perceive a change throughout the duration of the Code Next program.

In order to analyze the data in relevance to my research questions, I entered two collections of data into open-source statistics programs JASP to determine their descriptive characteristics and statistical significance. First, I entered the "before" PTSC scores and the "currently" PTSC scores, and ran a paired sample t-test. Then, in pursuit of understanding any perception differences between students who participated in the in-person "lab" version of the program and students who participated in the online version, I calculated the perceived changes between the PTSC scores ("currently" minus "before") for each of the two groups. I then ran a two-sample (or independent sample) t-test with those numbers after conducting a test for normality.

Validity and Credibility

I employed a number of tactics to support the validity and credibility throughout this research. While I conducted the follow-up interviews with students, I explicitly explained to the students that “there are no right or wrong answers,” utilizing phrasing like “you can help us make this program better by sharing your honest thoughts” and referring back to the study information sheet I provided. I encouraged candor and honesty, made frequent assurances that nothing bad could happen to students based on their answers, and reiterated that I am a “researcher” during interviews, rather than a Code Next lead. Furthermore, colleagues helped me gather the data for the surveys. As noted, Code Next staff administered the online survey to students, therefore creating a distance between the subjects of the survey (the students) and myself.

Early on in this process, I anticipated that readers may question my personal bias. In order to address that, I engaged in training on survey administration and interview methods, in order to better prepare myself on administering non-biased questions and follow-ups. I also read through previous studies conducted by Code Next’s external research partner, EDC, and asked a member of their team for recommendations. EDC researchers are 1) familiar with this afterschool program and 2) experts in this field of research—both key features of appropriate sources of information and guidance (Merriam, 2009).

Lastly, in order to ensure that my data collection methods were sound, reliable, and valid, I employed two tactics. First, I scored my survey with a systematic rubric. I awarded values to responses across several dimensions of the “tech social capital” index, therefore eliminating opportunities for loose interpretation of the data. Second, I conducted two pilots prior to the full launch of my methods. Pilots are useful in that they can test research design and allow for improvements to be made (Thabane et al., 2010). As such, I conducted pilot interviews with recent Code Next alumni during the fall of 2022; those same students then tested my survey in January of 2023. Given that they were alumni, these pilot students did not take part in the main study.

Positionality and Ethical Considerations

I anticipated several ethical concerns, including reactions to my positionality. I am a Code Next program manager, as well as a white woman (a member of a different race from the study's participants). This had potential to create issues, as students may have felt compelled and/or pressured to respond in a certain way. To quell that feeling, I compensated them upfront with payment for their involvement, and assured them that there was no pressure whatsoever to answer in a way they may have deemed favorable to me. For the interviews, which I conducted myself, I kept this study voluntary, shared my role as interviewer upfront, and emphasized that participants' answers do not impact their standing in the program. Additionally, rather than emphasizing my role as one of the Code Next leads, I stressed my role as a graduate student researcher, and shared that this research will potentially aid Code Next in becoming a better program. Additionally, surveys were shared by the lab/online program Community Managers—all individuals of color who possess trusting relationships with the students.

To address any additional ethical concerns, I anonymized the data, stressing to my student subjects that their information would be completely anonymized. I employed a willingness to address any and all concerns along the process, including releasing survey responders and/or interviewees from the process if they requested it at any time.

Conclusion

This study’s exploratory, mixed methods approach provided a multi-dimensional understanding of the complex nature of tech social capital. The next chapter discusses detailed analysis of the data and findings derived from that data.

Chapter 4: Findings

This study investigated the intersection of afterschool computer science education and "tech social capital" development. The exploratory sequential mixed methods study sought to first examine how Black and Latino/Hispanic high school students understand their network of relationships in their lives as it supports their engagement with computer science. Furthermore, the study sought to examine any student-perceived change in "tech social capital" during involvement in an afterschool computing program—Google's "Code Next" program, as well as whether there was any difference in that perceived change between in-person program participants and online program participants.

The investigation sought to address the following research questions:

1. How do Black and Latino/Hispanic high school students describe the network of relationships in their lives?
    a. How do Black and Latino/Hispanic high school students describe the impact of those relationships on their thoughts around computer science?
2. To what extent do Black and Latino/Hispanic high school students perceive a change in their tech social capital during an informal, afterschool computer science program?
    a. Does the extent of perceived change differ between participants who participated in-person vs. online?

To answer these questions, I first ran a qualitative portion of the study with a series of interviews. Information from those interviews was then used to create a survey intended to examine tech social capital for the quantitative portion of the study. In the following chapter, I first delve into the qualitative findings in greater depth. I then address the development of the survey from those findings. I follow that section with a discussion of quantitative findings from the survey completion. And finally, I discuss connections and between the quantitative and qualitative findings in response to my research questions.

RQ1 and RQ1a: Qualitative Findings

For the first part of the study, I conducted interviews with 20 Code Next students, nine of whom participate in the "live" in-person program, and 11 who attend the "Connect" online program. In Chapter 3, Table 3.1 summarizes interviewee demographics.

Overall, when describing their networks, Black and Latino/Hispanic high school students reported having at least one significant relationship that encouraged their interest in and exploration of computer science and STEM content, with every student reporting a significant relationship with an adult and almost every student reporting a significant relationship with a peer. Furthermore, almost every student reported that relationships with adults had contributed at least two resources related to helping them learn computer science, and that relationships with peers had contributed at least one resource to their lives. Students identified "introductions to programs," "access to physical technology and hardware," and "tutoring" as the resources most frequently attained through relationships with adults, and "tutoring," "links to helpful content or information," and "encouragement" as the resources most frequently attained through relationships with peers.

Relationships with Adults

Every interview participant described their networks as containing at least one adult in their life that helped or encouraged them to get into computer science. In their interview, students referenced several overall codes—17 mentioned "family" relations, 10 discussed "formal school" relations, and 9 referenced "afterschool program" relations. Seven students also referenced individuals falling into a general "other" category, which included a local librarian, a foster care agency rep, a church member, a corporate STEM education volunteer, and a college recruiter.

Out of the 17 students who referenced “family” adults as significant in their networks, 16 mentioned “parents/guardians,” the most-heavily referenced term. Following that, 6 students mentioned non-nuclear relatives (aunts, uncles, older cousins), 5 mentioned family friends, and 3 mentioned grandparents.

Parents/guardians came up several times as an impetus or reason for why students started to pursue or explore computer science, with several participants referencing their parents/guardians as an “inspiration,” “encouraging,” or “introducing.” When describing their parents/guardians this way, many students described a common situation where their parents/guardians would notice a budding interest and encourage it. For some students, this enabled them to believe they could pursue a career in the field and move up in the career space; one student’s mother expressed that “Puerto Rico is not the end” and that pursuing computer science was “a gateway to a better future.” For others, it was more about general support. For one Black male student, whose mother had some technical experience, the experience of having someone “root” for him was more important that the technical support, as he describes:

> *[My mom] was always there on the sidelines, rooting me on. She never really doubted me or anything. She always believed in me and she encouraged it instead of saying “I don't think this is a good idea.”*

Others described parents who supported them no matter their interest. For example, one Latina female explained that her parents had no thoughts or preference over whether she pursued computer science or something completely different:

If I want to do it, they'll support me and if I don't want to do it, they'll say it's all right, you know, at least you tried it.

Aside from sheer encouragement, many participants reported that their parents/guardians had experience in the tech space or as technology users, which they shared with their children. However, a few parent connections proved significant without experience in the computer science space, as one respondent described:

I would say definitely my aunt and my mother, not just in the fact... They, they don't do anything that is technology-wise. But they're like, always there to take me places and ready to pay for whatever it needs to get done for me to do things.

The same proved true for non-nuclear relatives, family friends, and grandparents, with most respondents sharing stories of the impact of a family adult's connection with technology ("My uncle always had me around technology and always showed me how certain things worked, like laptops and computers"), and a small few sharing the importance of relationships without technical experience.

Out of the 10 students that referenced "formal school" relations as significant in their networks, "teachers" presented as the most-heavily referenced term at 9 mentions. Most of the teachers referenced deliver STEM subject material (science, technology, engineering, math) and teach at the high school level, though a few fell into the elementary and middle school categories. Students largely described their teachers as introducing them to the general concept of "computer science," with some referencing more specific, individual topics like "coding," "3-D modeling," "robotics," and "cybersecurity." Many of the students also described their teachers as fundamentally focused on providing instructional and "problem solving" support, as well as providing encouragement related to learning and completing tasks. Here's an example from one student:

> *[My computer science teacher] could tell I liked, like, coding and stuff, and told me to keep doing more coding classes in the future… When I needed help, I asked her questions. And she helped me.*

Out of the 9 students who referenced "afterschool program" relations as significant in their networks, most of them described an afterschool program educator, typically called a "teacher," "coach," or "mentor." Each educator referenced served in an afterschool program that delivers STEM-related content. Represented programs included regional instances for nationwide afterschool programs (Code Next, Black Girls Code, Girls Who Code, FIRST Robotics, The Knowledge House), university-sponsored programs (University of Puerto Rico CyberCamps, Cooper Union STEM Camps), and one-off, local afterschool programs (All Star Code, bootcamps, robotics program run at school after-hours). Students often described these educators as providing both encouragement and instructional support, similarly to the formal teacher category, but with an increased focus on technical "debugging" (error fixing) and relevant computer language skills. As one male Latino student described:

> *One of the coaches in Code Next, Jeremy… he's talking about Python, like how there's the common misconception that like it's, it's a first language you need to learn. He kept talking like, "Never listen to that BS. Like, Python is like a scam. That's something you find on the backend." And I'm like, "Oh, I never knew that."*

The particular quote is also helpful in that it signals how students get access to information that demystifies the tech sector for them, revealing shortcuts or inefficiencies that others with connections to the coding world may already know.

Students further reported a feeling of “inspiration” from afterschool program adults who had served in the computer science field themselves, naming certain individuals as “role models” that they looked up to:

> *Deyby has been a Code Next instructor… I’m, like, really proud of him for that. So it’s just like, that’s someone I strive to be, I guess—kind of like my role model.*

A few students also described that individuals in this category pushed them to move forward or consider additional computer science or general STEM education opportunities, such as starting with an introductory coding class and moving into an advanced class.

More generally, across all categories, students reported that these adult relationships helped them understand the application of computer science knowledge in the job world, as well as how it differed from—and sometimes proved more fruitful—than other job pathways. One Black female student, for example, described that her relationships with her family members and teachers “pushed [her] more to get a job in computer science” because she could see "really how it could, like, improve [her] work-life balance.” Another student explained that he wasn’t even planning on going into the computer science field at first, but a high school teacher of his introduced him to different computer science fields, including game creation, software development, and “even cybersecurity.”

Relationships with Peers

Almost all interview participants described their networks as containing at least one peer who helped or encouraged them to get into computer science. Specifically, 19 out of 20 referenced a peer, with the most heavily-referenced code as peers from “formal school” at 13 mentions. Following, codes included “family” peer relations at 11 mentions, “afterschool program" connections at 6 mentions, and 2 mentions in the "other" code category (one relationship formed through church and one through online gaming).

Out of the 13 students who referenced "formal school" peers as significant in their networks, non-STEM class friends presented as the most-heavily referenced term at 11 mentions, followed by friends met in STEM classes at 4 mentions. Although the "non-STEM" signifier means that students did not meet these individuals in a shared science, technology, or computer science class, in most cases friendship formation and/or bonding did take place over mutual interests in technology or computer science topics. For example, several of the individuals mentioned a shared interest in video games:

> *Me and my friend were playing a game, right? And playing Minecraft, and, we used to see these videos where like people would create like… mods, modifications for the game that would like change some of the aspects of it, and then like, you know, make it more fun like to our eyes. And we were like, "Oh that'd be cool to make."*

Some students also mentioned that while they had long histories with non-STEM friends, they learned about technology or computer science topics when their friend began to practice coding with "passion" or described it as "cool."

Out of the 11 students that referenced "family" peers as significant in their networks, "siblings" presented as the most-heavily referenced term at 8 mentions, followed by non-nuclear relatives (peer-age cousins) at 3 mentions and peer-age family friends at 2 mentions. Relationships with siblings proved similar to friends in that students would report the impact of a sibling expressing interest in technology or computer science topics as introductory. Several mentions of siblings also indicated that, especially in the case of older siblings, there was "influence," "encouragement," and "inspiration" for a younger sibling, especially when a sibling took classes, pursued a computer science major in college or worked in the field. However, even if a sibling didn't pursue a STEM-specific pathway, a few students described the encouraging sensation of seeing what was possible:

> *[My sister] just inspires me, because like, she has, like, I don't know how she did it. Like it truly amazes me how, like, she can go to college, without paying anything, and it just… like it inspires me to do my best.*

The "afterschool program" connections code, which included 3 mentions from sports relationships and 3 mentions of STEM program relationship, fared similarly to the "formal school" peers group. All six students mentioned that contacts formed through these programs introduced them to new or additional STEM or coding content, as the peer in question was either learning coding, enrolled in a program, or willing to provide help or support.

More generally, across all categories, almost all of the interviewees described that their peer relationships contributed a sense of "camaraderie" or "encouragement" to their lives. For some, finding a peer who likes computer science, or a "like-minded person at my age" as one Black female student described it, provided thought partnership and "strengthened the want to work in the field" without having to do it alone. For others, having a peer with similar interests validated their own, along with a "If they can do it, I can do it!" boost of confidence. But even in the cases where peers did not have interest or expertise in computer science, students still received encouragement and support, as one student explained:

> *They always encouraged me to, like, double down on what I'm good at, what I like, you know… find compromises in between what you know and what you're really good at. "You like coding and everything like that, and you seem to enjoy yourself, so like, why not go with that, right? See where it takes you!"*

A couple of students also described that their peers widened and deepened their understanding of computer science content and jobs, though not to the same degree as with adult relationships. One Latina female student, for example, described that her friends had a variety of interests in the computing world, showing her that there is "more than just one section of computing and coding."

Resources Acquired Through Adult Relationships

Almost all interview participants (19 out of 20) reported that their relationships with at least one adult contributed at least one resource related to helping that student learn computer science, with the most commonly-mentioned resource codes being "introductions to computer science programs," "access to physical technology or hardware," and "tutoring." In total, out of the 19 interviewees who reported that an adult contributed a resource, six students reported access to two resources, six students reported access to three to four resources, and seven students reported access to five or more resources through adult relationships.

Overall, the most commonly-mentioned resource attained through relationships with adults was introductions to computer science programs (16 mentions). Most of the students described that at least one of their adult connections connected them to, recommended them for, or pointed them in the direction of free coding camps, internships, or afterschool programs. In some cases, the adult recognized an interest or passion in the student, referencing that as an impetus for the recommendation. In other cases, the adult signed the student up directly, which led to the development of the interest or passion, as one Latino/Hispanic male student explains:

> *So my mom signed me up for this coding bootcamp. At first, I was like, kind of unsure about it. I wasn't sure how it was gonna go. And yeah, that's pretty much it… After the coding bootcamp, I just fell in love with coding and all that.*

Additionally, more than half of the students mentioned access to physical technology or hardware (14 mentions). While only two students mentioned "money" as a received resource throughout the interviews, access to digital equipment like computers, 3-D printers, robotics kits, and VR headsets dominated the conversation. Most of the students who mentioned hardware described a computing device (a "computer," "laptop," or "PC") as the primary form of technology. In cases where the adult relationship in question was with "family," "access" mostly came in the form of a parent or family member gifting a piece of technology, such as what one Black female student describes: "My mom got a new desktop for Black Friday, but before… like, I had no computer at all." In cases where the adult relationship in question was a "formal school" or "afterschool program" relationship, access to technology was often conducted through lending or borrowing technology, as one Latino/Hispanic, non-binary student shared:

> *"Well, [my teacher] just gave us access to the computers, and I guess every part of it, the breadboard, the motors. He gives all of it because he was in engineering. But we're able to play with those when he was our teacher."*

More than half of the students also mentioned tutoring (12 mentions) as a resource obtained through adult relationships. "Tutoring" as a code describes any reference to either individual or group instruction that introduces students to computer science education knowledge. In most cases, the adult in the relationship was the one providing the tutoring or instructional support, typically through a one-on-one setting with the interviewee; the adult oftentimes had experienced with the content the student learned about, such as software engineering expertise. In a few other occasions, the adult directed or provided the student with access to tutoring programs, such as through a university.

Other resource mentions from more than one-third of interviewees were “access to software” at 9 mentions and “relationships or connections” at 8 mentions. Similarly to physical hardware, “access to software” referred to paid software (not free websites or programs) that adults either gifted to students or allowed them to use. While some of these items, like TinkerCad and AutoCAD, are used specifically for computer science or engineering education, others mentioned are more generic software subscriptions, like writing or editing software, that can be used adjacently to other programs, as one Black male student described:

> *My dad purchased me a Microsoft 360 subscription, for like Adobe After Effects and all that stuff, for editing videos and everything, like Photoshop.*

“Relationships or connections,” on the other hand, do not possess an inherent financial value. Rather, this code describes instances where students referenced adults helping them to expand their networks and meet industry professionals or students in technology. These connections provided examples of success and real-world skill application, as well as opportunities to access even more resources, as this Black male student described:

> *And [my AP Computer Science teacher] brought this one person who owns this one program in Seattle, where you have to be 21. You’re able to go to this little college thing, and then they help you get internships.*

A few last mentions of resources came into conversation, namely “links to helpful content or information” (6 mentions) and “money or payment” (2 mentions). One unique resource came in the form of “encouragement” at 5 mentions. Whether “encouragement” can be described as a “resource” is a source of debate, students defined it as a resource and named it as something they valued as a “key factor” in sticking with computer science education. In fact, one student credited it as the reason that she and her friends did not drop out of the Girls Who Code program, explaining that when a coach of hers would check in, she felt like she had someone "looking out for us." This code also came up a number of times when discussing resources attained through peer relationships, which will be further explored in the next section.

Resources Acquired Through Peer Relationships

Almost all interview participants (19 out of 20) reported that their relationships with at least one peer contributed at least one resource related to helping that student learn computer science. In comparison to resources attained through adult relationships, peer-attained resources tended to be slightly lower in total number; out of the 19 interviewees who mentioned a peer-provided resource, seven students reported access to only one resource, while eight students reported access to two resources, and four students reported access to three to four resources through peer relationships. Furthermore, unlike the top resources provided through adult relationships, the most commonly-mentioned resource code through peer relationships was "tutoring," followed by "links/helpful information," and "encouragement." Notably, none of these top resources had any financial cost or monetary value, yet the interviewees deemed their intrinsic value as helpful or significant.

Overall, the most commonly-mentioned resource attained through relationships with peers was "tutoring" (10 mentions). While the aforementioned tutoring in the adult relationship section combined both one-on-one and group support, tutoring in the peer relationship category related solely to one-on-one support, where peers would engage in pair coding or share their code or content, as in this example:

> *We were doing "Creative Coding," and I couldn't figure out how to get the ball to bounce off the wall. So, a girl named Destiny and then my friend Elijah, he was… they were both like, "Ok, well, let's just compare all of our all of our code," and then we figured it out.*

In most mentions, “tutoring” came from a peer who was either enrolled in a program simultaneously as the interviewee, or had content knowledge that supported the interviewee’s desire to improve. And while that content knowledge was typically STEM-related, there were a few exceptions, such as one student describing his sister’s guidance on college applications.

“Links to helpful content or information” was a close second in the list of most commonly-mentioned resources attained through relationships with peers (9 mentions), slightly higher in number than the 6 mentions from the adult relationships section. While access to hardware and access to software received few call-outs (3 mentions and 2 mentions, respectively), students acknowledged that their peers introduced them to free, helpful online resources. Many of the links fell into the video (usually YouTube) or article tutorial category, as one Black female student described:

> *He helps me find some videos on YouTube or something to explain to me. And he uses some articles sometimes. To, like, fix errors, like certain errors I might have.*

Beyond those links, other mentions included free websites and software like Khan Academy, editing applications, and Minecraft—all accessible without paying.

Other codes included “introductions to programs” at 5 mentions and “relationships and connections” at 2 mentions, while once again, “encouragement” got acknowledged by 6 interviewees. According to students, even when a peer could not provide any of the aforementioned resources, their encouragement or moral support was useful and impactful, as one Latino/Hispanic male student relayed about a friend of his:

> *And even though like a lot of times, I'm talking all this technical jargon to him and he's just sitting there… he'd always encourage me, you know, he'd always say, “That’s a really good idea. You should get into this.”*

Updates to Chen Instrument Based on Qualitative Findings

As mentioned in Chapter 3, upon completing the coding process for the qualitative analysis, I adapted the Chen Personal Social Capital Scale survey instrument (Chen et al., 2009) and created a Personal Tech Social Capital (PTSC) survey instrument, presented in Appendix C.

Chen's instrument includes two forms of questions: questions that address "bonding social capital," and questions that address "bridging social capital." The bonding questions ask the survey taker to select a number for each type of person, such as "family members" or "friends," while the bridging questions describe resources, such as "wealth" or "broad connections with others." Given the focus on computer science and the utilization of student voices in the survey adaptation, both types of questions received updates to phrasing and number of options. In adapting the language of Chen's survey to this newer version, it is important to note the changes in question items based on student language and description. As demonstrated in Appendix A, there are a number of phrases, such as "family friends," that students use regularly in their interviews. As such, I changed the language of the survey items to better match students' views of the world.

For the bonding questions, the Personal Tech Social Capital (PTSC) instrument increased the number of items from six to eight, as well as the variation of those items, as seen in Table 4.1. The number and naming of items increased based on the popularity of certain sub-codes shared across the analysis in Appendix A—namely "parents/guardians," "siblings," and "teachers/coaches." It was also important to be slightly more specific in the naming of these groups to reflect how the students referenced certain types of individuals, such as students differentiating between "extended family" members and "family friends" as opposed to Chen's more generic “relatives.” This proved useful as well when reviewing some of Chen’s options; “relatives,” for example, appears too similar to his mention of “family members.”

For the bridging questions, the Personal Tech Social Capital (PTSC) instrument again increased the number of items from six to eight, as well as the variation of those items, as seen in Table 4.1 below. The number and types of items increased based on the frequency of certain sub-codes shared amongst the qualitative “adult relationship” and “peer relationship” analysis, including “technology or hardware” and “expertise or the ability to tutor you.” The nature of several of the items also includes more explicit reference to computer science, as opposed to Chen’s more generic terms like “political power” or “a professional job.”

Table 4.1
Instrument adaptation

Original survey instrument + question example *Chen’s Personal Social Capital Scale*	**New survey instrument + adapted question** *Personal Tech Social Capital (PTSC)*
Bonding Question Among the people in each of the following six categories, how many can you trust? -Your family members -Your relatives -People in your neighborhood -Your friends -Your coworkers/fellows -Your country fellows/old-classmates	*Bonding Social Capital Question (PTSC-Bo)* ***Before you started in Code Next,*** among the people in each of the following six categories, how many *did you trust enough to talk with about computer science?* -Parents/guardians -Siblings -Extended family (aunts, uncles, grandparents, cousins etc.) -Family friends -Teacher/coaches from school -Teacher/coaches from outside of school -Friends from school -Friends from outside of school
Bridging Question	*Bridging Social Capital Question (PTSC-Br)* ***Before you started in Code Next,*** of all of the people you thought of above, how many of them *possess the*

When people in all the six categories are considered, how many possess the following assets/resources? -Certain political power -Wealth or owners of an enterprise or a company -Broad connections with others -High reputation/influential -With high school or more education -With a professional job	*following resources?* -Technology or hardware -Software -Relationships or connections to people in tech -Willingness to provide you encouragement or moral support -Links to helpful information or websites -Money -Knowledge of computer science programs or opportunities -Expertise or the ability to tutor you

Additionally, the Likert scale changed from an "all, most, some, a few, none" ordinal scale to a "0, 1, 2 to 3, 4 or more" ordinal scale. Again, similar to the lack of clarity between some of the wording in Chen's instrument (such as the difference between "family members" and "relatives"), the use of terms like "all" or "some" can be harder for students to differentiate between. An ordinal scale with numeric values creates more ease and leaves less room for personal interpretation when students are asked to quantify numbers of relationships or resources.

As referenced in Chapter 3, respondents received a PTSC score for the first section of questions, as well as a PTSC score for the second section. This approach allowed for comparison of the two scores, and for understanding how students perceive a change throughout the duration of participation in the Code Next program.

RQ2 and RQ2a: Quantitative Findings

Overall, surveyed Black and Latino/Hispanic high school students (n=88) reported a statistically significant increase in their tech social capital during an informal, afterschool computer science program. A Cohen's *d* calculation indicated a large effect size, demonstrating the practical significance of the outcomes from this survey. Descriptive statistics for all participants can be seen in Table 3.1 in Chapter 3, and a comparison between online and live survey-takers can be seen in Table 3.2.

The sample also showed that the extent of that perceived change differed between students who participated in the in-person "lab" version of the program and students who participated in the online version. More specifically, in-person students perceived a higher and more positive impact on their tech social capital than online students. However, a Mann-Whitney U test indicated that these results were not statistically significant.

Change in Perceived Tech Social Capital

Analysis of the survey demonstrates that Code Next students did perceive a positive change in their overall tech social capital during their participation in the program. According to the analysis, there was a statistically significant increase (4.658) between the mean of "before" PTSC scores (12.000) and the mean of the "current" PTSC scores (14.658), $t(87) = -8.038$, $p < .001$, as demonstrated in Table 4.2. I calculated a Cohen's d to assess the effect size of the paired sample t-test. The result was 0.88, indicating a large effect as $d > 0.8$. This implies that the difference between the means of the groups is practically significant.

Table 4.2
Descriptive statistical analysis for "before" and "current" PTSC, PTSC-Bo and PSTC-Br scores

	Mean	*SD*	*Min*	*Max*	*Med*
"Before" PTSC*	12.000	2.887	6.000	19.250	11.625
● PTSC-Bo only	5.283	1.488	3.000	10.750	5.000
● PTSC-Br only	6.717	1.819	3.000	10.875	6.688
"Current" PTSC*	14.658	3.150	6.375	20.750	15.188
● PTSC-Bo only	6.115	1.535	3.000	9.500	5.875
● PTSC-Br only	8.543	2.058	3.375	12.000	8.938

**n=88*

When further breaking down the data into PTSC-Bo scores for bonding-only values and PTSC-Br scores for bridging-only values, there was again a positive perceived increase in both forms of tech social capital. However, the perceived increase was larger for PTSC-Br than for PTSC-Bo. As shown in Table 4.2, the PTSC-Br mean increased from 6.717 to 8.543, indicating a positive change of 1.826 ($t(87) = -7.481$, $p < .001$). In both cases, there was a statistically significant increase.

Table 4.3
Paired t-test for "before" and "current" PTSC, PTSC-Bo and PSTC-Br scores

Measure 1 / Measure 2	*t*	*df*	*p*
"Before" PTSC / "Current" PTSC	-8.038	87	<.001
"Before" PTSC-Bo / "Current" PTSC-Bo	-6.328	87	<.001
"Before" PTSC-Br / "Current" PTSC-Br	-7.481	87	<.001

As with the *p*-value from the first *t*-test, the *p*-values for each of the "before" and "current" PTSC-Bo and PTSC-Br scores were <.001, as shown in Table 4.3. Again, I calculated Cohen's *d* to assess the effect size of the paired sample t-tests for PTSC-Bo and PSTC-Br. For PTSC-Bo, Cohen's *d* was 0.55038, indicating a medium-to-large effect. For PTSC-Br, Cohen's *d* was 0.940181, indicating a large effect.

Difference in Perceived Change Between In-Person Students and Online Students

According to descriptive statistical analysis on the samples, as shown in Table 4.4, in-person students reported a mean increase of 3.319 between their "before" and "current" PTSC scores, while online students reported a mean increase of 2.155, as shown in Table 4.4. However, there were no statistically significant differences between the two groups.

Table 4.4
Descriptive statistical analysis for in-person and online changes in PTSC scores

	Mean	*SD*	*Min*	*Max*	*Med*

In-person students*					
● PTSC change	3.319	3.328	-2.750	9.625	2.688
● PTSC-Bo change	1.211	1.171	-0.500	3.750	1.000
● PTSC-Br change	2.109	2.522	-3.000	7.875	1.875
Online students**					
● PTSC change	2.155	2.850	-2.625	7.875	1.500
● PTSC-Bo change	0.545	1.213	-2.375	3.500	0.500
● PTSC-Br change	1.610	2.095	-1.875	6.000	0.688

**n=38 / **n=50*

Distributions of the engagement scores for online and in-person students were not similar, as assessed by visual inspection and the Shapiro-Wilk test. While the data does suggest a difference in perception between the sample of in-person and online students, these differences are not statistically significant. Because the data were not normally distributed as demonstrated by both a visual check and the Shapiro-Wilk test, I ran a Mann-Whitney U test to determine if there were differences in PTSC scores between the online and live students.

The Mann-Whitney U t-test resulted in a *p*-value of 0.104; given that the *p*-value is > 0.05, there is not enough evidence to reject the null hypothesis, and the difference between the two groups is not statistically significant.

Overall Synthesis of Findings

Connection Between Qualitative Findings and Quantitative PTSC Score Outcomes

Outcomes from the quantitative analysis indicated that students perceived an increase in their tech social capital networks, with a Cohen's *d* test indicating a large effect size. Upon further analysis, survey respondents indicated a larger perceived change in bridging capital, measuring the number of accessible resources, than that of bonding capital, measuring the number of significant relationships.

Specifically, looking deeper into the interview responses provides an explanation for this, as in several cases, a relationship with one individual led to the acquisition of multiple resources. One Latina student, for example, described how her relationship brother brought her three resources in the form of software, tutorials, and tutoring:

> *"He came with Unity, um, and oh, he would give me, like, tutorials to follow. Like he had tutorials that he followed, and he was like, "Oh you should probably do this one because this one really helped me," and I was like, "Okay then I'll do that, too."*

Another Black male student described how in his case, the afterschool mentors he met through the Code Next program simultaneously introduced him to connections and tutored him on networking, meaning he gained both new relationships and new skills:

> *There's so many different connections within this one connection. Right? And… these people that are like teaching you how to network and stuff… They're like the ones who are really showing you the real, real insight.*

For any student, one relationship can multiply the magnitude of impact on a student's tech social capital when that relationship contributes multiple resources to that student's life.

Connection Between Qualitative Findings and Live/Online Perceptions

Out of the 20 Code Next student interviewees, nine came from the in-person lab program while the remaining eleven were online students. Upon revisiting the interview codes, there were clear differences between how each group described their social capital that provide support for the PTSC survey results.

Notably, in terms of bonding capital, relationships with teachers/coaches from outside of school came up most frequently in references amongst the in-person interviewees, while relationships with family (adults) came up most frequently amongst the online students.

An additional element of note is the different perspectives on resource acquisition and bridging capital. Amongst in-person interviewees, technology/hardware took the top reference spot, while almost every online interviewee referenced knowledge of computer science programs or opportunities. Increasing access to technology and hardware, like computers or 3-D printers, is much easier when joining an afterschool program in a lab or classroom. It is also the lone resource on the list that benefits from having an institutional backer. As one Black student described, she received access to hardware through her school when in a particular class or with a specific teacher:

> *"At my old school, middle school, we had 3D printers, and they were in the library. So the librarian, she and I would go in there basically every day and mess around with the 3-D printers and learn it, and get to know and basically, just understand the program behind it."*

"Knowledge of computer science programs or opportunities," on the other hand, is something that can be acquired whether a student is physically in-person or online.When a student takes part in a live computer science program, there are more likely to get increased access to new resources like hardware, unlike other items that are easily shared online or cost little to no money.

Conclusion: Principal Findings

The findings from this study demonstrated the importance of social capital networks in Black and Latino/Hispanic high school students' lives. Analysis of the data presented five key findings.

The first three key findings related to RQ1 and RQ1a. First, students reported having at least one significant relationship that encouraged their interest in and exploration of computer science and STEM content, with every student reporting a significant relationship with an adult and almost every student reporting a significant relationship with a peer. Second, almost every student reported that relationships with adults had contributed at least two resources related to helping them learn computer science, and that relationships with peers had contributed at least one resource. Third, students expressed that these relationships had a largely positive impact on their interests in and around computer science.

The next finding relates to RQ2 and RQ2a. Black and Latino/Hispanic high school students perceived an increase in their tech social capital during an informal, afterschool computer science program; this finding was buoyed by a large Cohen's *d* effect size.

The last key finding addresses intersections and shared evidence regarding both research questions. Code Next students' perceptions of higher bridging social capital growth over bonding social capital growth may be due to the multiplicative nature of relationships, in that a single relationship can contribute multiple resources to a student's life.

Chapter 5: Discussion

I have held a number of roles in both education and technical spaces—as a STEM educator, a school administrator, an edtech journalist, and a computer science education program manager at a technical Fortune 500 company. Along the way, I have seen that workforce development, especially for the tech-based workforce, starts at a young age. But more importantly, I see that success and economic mobility in the working world comes down to not just what you know, but oftentimes, *who* you know. That relationship between "social relations" and "finding a job" (Lancee, 2012; Piracha et al. 2016, Faucher, 2018) in the tech world grows stronger with each passing year, yet representation from Black and Latino/Hispanic talent remains stagnant (Margolis et al., 2018; Bureau of Labor Statistics, 2021; Davis et al., 2021).

This study sought to explore *tech social capital*—relational social capital benefiting learners as they move through the computer science ecosystem—within Black and Latino/Hispanic high school student communities. Utilizing a mixed methods study, I explored how Black and Latino/Hispanic high schoolers described their networks of relationships and resources, and whether these students perceived a change in their subsequent tech social capital during an informal, afterschool computer science program. From it, I garnered several learnings intended to encourage K-16 educators, researchers, and communities to pay more attention to the social capital construct, identify opportunities for measurement, and provide students with an opportunity to share their own insights into social capital development.

The analysis of data revealed five key findings, as reported in Chapter 4. In this final dissertation chapter, I first discuss those findings, pulling out four overarching themes. I then explore this study's limitations, including sample and research design/scope limitations. Following, I lay out implications for stakeholders, including K-16 educators and researchers.

Lastly, I end with suggestions for future research, plans for research dissemination, and concluding thoughts.

Discussion of Major Findings

Throughout his writings, Pierre Bourdieu described that social capital can be broken down into two parts: relationships (or bonding capital), and the quality and amount of those resources afforded through relationships (or bridging capital). He additionally explained that social capital can both further an individual's success in education and career, and be convertible to economic capital under the right conditions (Bourdieu, 1986). This study's interview questions and ensuing survey sought to identify changes in each of those bonding and bridging categories, respectively (Bourdieu, 1986; Claridge, 2018), through the eyes of the students in possession of that capital. In re-analyzing the findings discussed at the conclusion of Chapter 4, four major themes emerged: the opportunities for afterschool programs to provide significant tech social capital in the form of "institutional agents" and access to technical technical hardware; the myth of the deficit tech social capital mindset; the potential for differences between live and online learning environments; and the utility of quantifying tech social capital for more common use.

What Afterschool Programs Can Provide

<u>Institutional Agents</u>

The first theme focuses on findings related to RQ1, RQ1a and RQ2, from the perspective of how afterschool programs can better support students in their tech social capital development. Specifically, afterschool programs provide 1) opportunities to develop relationships with institutional agents and 2) access to technical tools and hardware.

According to this study, students described their networks as having significant adult and peer relationships, and perceived that their tech social capital increased during engagement in an afterschool computer science education program. Given the limited number of social capital studies conducted about afterschool programs (Search Institute, 2020; Booth & Shaw, 2020), this study suggests these afterschool, non-formal learning programs can indeed serve as social capital brokers—and one bright spot comes in the form of relationships with educators/coaches.

As scholars like Ricardo Stanton-Salazar (2011) describe, afterschool educators can become *institutional agents* who broker more learning opportunities and resource acquisition. When describing adult relationships that affected their thoughts about computer science, both interviewees and survey takers named familial relationships as vital. However, while students are surrounded by adult family members from birth, the number of significant familial relationships is less likely to increase than relationships in afterschool computer science programs, where students have the chance to meet new adults with computer science expertise. Stanton-Salazar (2011) describes institutional agents as individuals who can both increase motivation and access to resources, and in the case of Code Next, these adults can provide unique and specific insights and resources to the computer science industry.

That being said, it should be noted that institutional agents do not replace or overtake the importance of family members in students' lives (Rodriguez et al., 2023). Yosso's community cultural wealth framework (2005) acknowledges the importance of family members and their contributions to an individual's cultural wealth. Yosso explains that family members can become significant sources of support and knowledge that contribute to a person's overall well-being and success.

The concept of "institutional agents" applies to peer relationships, as well, in that individuals met through afterschool programs can provide similar motivation and access to resources, which is buoyed by existing research (Frank et al., 2008; Jin et al., 2018).

Findings garnered through the study suggest that education programs should place more emphasis on developing these relationships with institutional agents—not only because of the motivation factor, but also because of the potentially multiplicative nature of these relationships in regards to resource acquisition. In the study, we saw a more substantial increase in bridging capital (2.109 increase for in-person, 1.610 increase for online) amongst PTSC survey takers over bonding capital (1.211 increase for in-person, 0.545 increase for online). Relationships formed through afterschool programs can produce multiple resources for an individual, as one student quoted in Ch. 4 embodied when he said, “There’s so many different connections within this one connection.”

<u>Tech-Centric Resources</u>

Afterschool programs also have the ability to provide access to digital and technical resources unique to the computer science space, like complex hardware. As discussed in Chapter 2, afterschool programs have fewer limitations in what and when to teach and assess (Rodrigues, 2009; Roberts et al., 2018), including how they choose to spend their budgets. As such, there is more flexibility to spend on tech-centric materials like computing devices, 3-D printers, and state-of-the-art software. In this study, students took note of that—calling out “access to physical technology and hardware” as a resource of note obtained through Code Next. While resources like “tutoring” and “links to helpful content or information” are just as impactful in a student’s life, afterschool programs with budgets dedicated to computer science education yields greater “access to physical technology and hardware” than resources acquired through familial or peer relationships.

The Myth of the Deficit Mindset

While afterschool programs provide fruitful opportunities for tech social capital growth, this study underscored a second conclusion—students are anything but tech social capital-deficient when they enter afterschool computing programs.

As described in Chapter 2, many social capital studies put forth a deficit approach in regards to student social capital, especially when studying students of certain racial or socioeconomic demographics (Harper, 2010; Puccia et al, 2021). This study avoided that sinkhole by integrating Yosso's community cultural wealth framework into its methodology, integrating the student perspective and thus avoiding the assumption that some individuals are inherently "wealthy" with capital while others lack it (Yosso, 2005). Perhaps unsurprisingly, in this study, every single survey taker reported a PTSC measure higher than zero when describing the time "before you started in Code Next," with a mean score of 12.000 (shown in Table 4.2). Essentially, students entered the program already in possession of some form of bridging and/or bonding social capital.

Furthermore, a major portion of those numbers related to student relationships with family members or other important connections who somehow influenced the student's computer science interests and exploration, a reality buttressed by the qualitative interviews and newer research. More recent higher education research hit on this point, such as one study by Rodriguez, et al. (2023) that suggested that Latina college students leveraged skills and knowledge acquired from familial relationships to succeed in unfamiliar computing spaces. As discussed in Chapter 4 and alluded to in the earlier "Institutional Agents" section, even in cases where non-computing family members or peers lacked technical expertise or connections to the computer science world, some still played a role in that student's life and subsequent computer science interests. One Black female student, for example, described that her non-computing parents saw her interest in art and encouraged her to consider “graphic design,” which turned into a gateway to computer science. Another student described how his high school friend chose to pursue music instead of anything STEM-related, yet was the one who directed him towards an architecture class at their school, which included an introduction to 3-D modeling.

At the end of the day, this study demonstrated a few key points—Black and Latino/Hispanic students already possess tech social capital prior to engagement in afterschool or formal education computing programs, and it is worth further exploring how to broaden definitions and understandings of applicable social capital to include students’ close familial ties.

The Realities of In-Person vs. Online Learning

The third theme addressed RQ2a, “*Does the extent of perceived change differ between participants who participated in-person vs. online?*” As explored in Chapter 4, few studies draw a direct comparison between online and live programs for social capital development, though some do acknowledge the need for more studies (Williams, 2017). In this study, qualitative data, although exploratory, suggested that in-person students may be better positioned for social capital development than their online peers, given their access to physical hardware and devices. While the survey’s results were not statistically significant when comparing online and in-person Code Next students’ PTSC scores, the survey provided a first glance at the potential for how live programs may outperform their online counterparts. Considering the swift movement of learning programs to an online environment given COVID from 2020-2023 (the same years of this dissertation’s evolution), this study’s results demonstrated an ongoing need for studies like this, with more sample sites and larger sample sizes.

The Need to Further Explore the Quantification of Tech Social Capital

The final theme presented amongst this study's findings related to the potential for tech social capital survey creation and effectiveness, speaking mostly to RQ2 and RQ2a. Chapter 2 explored the variety of ways education researchers have either avoided or attempted to quantitatively measure social capital (Abbasi et al., 2014; Search Institute, 2020; Chetty et al., 2022), yet also identified a scattered approach to the topic. Many education studies vary in social capital measurement approaches, and some refrain from identifying a social capital measurement or index at all. Meanwhile, sectors like public health and sociology have produced validated indices like the "Personal Social Capital Scale" (Chen et al., 2009) and Cohen's "Social Network Index" (1997). This study took a fruitful first attempt at adapting an existing social capital survey from a non-education industry and repurposing it to create a tech social capital index, specifically for the afterschool computer science education space—and with a non-deficit, student-centered framework. While this study is exploratory, and more studies are necessary to validate this survey instrument as a measure of tech social capital, it provides a foundation to build upon. This suggests that adapting existing social capital surveys for measuring tech social capital amongst Black and Latino/Hispanic students is feasible, and worth further exploration.

Study Limitations

While this study provided significant learning opportunities, several limitations may have influenced the outcomes of this research and/or affected the ability to apply the learnings to the average Black and/or Latino/Hispanic high school student.

One of the more obvious limitations was the sample size number, specifically as it pertained to the quantitative portion of the study. While procuring subjects for the interview part of the study proved easy, obtaining equal representation between online and in-person students for the survey was more difficult. This may have been due to the fact that online students (n=50) are used to receiving email correspondence from Code Next staff, while in-person students (n=38) are used to receiving more instructions from live interaction.

Additionally, part of the sample size issue was due to the time constraints associated with Code Next's quarterly schedule. The survey was ready for use in mid-March with only one week left in the winter quarter before students went on break, at which point students detach from email until spring quarter. In order to capture student responses before the break, I administered the survey for that last week only. Unfortunately, the last week of the quarter proves busiest for Code Next students, as they rush to finish their final projects. Thus, the limited time may have resulted in lower numbers of responses.

Other limitations emerged in the sample beyond sizing issues. First, the sample did not represent the average Black and/or Latino/Hispanic high school student, given the "opt-in" and availability factors nature of Code Next. Code Next participants choose to participate in the program and identify whether they prefer the in-person or online experience; more specifically, they fill out an application and either complete an online challenge (for the online program) or take part in a live interview (for the in-person program) in order to apply for a spot. Second, students choosing to come to the program possess the ability to attend. As a result, the sample set I used does not include students who cannot attend Code Next because of other responsibilities, like working an afterschool job or taking care of family members. These "opt-in" and availability factors means students are willing and able to engage in the afterschool program, while there are many students who otherwise might not be able to or choose to participate.

While the purposeful sampling techniques were conducted in order to give all students in Code Next equal opportunity to participate, certain obstacles may have kept some Code Next students in rural communities from participating in the study. For example, since the quantitative survey was only open for a week, some students in more rural communities like Puerto Rico and certain Southeastern cities may not have been able to access the survey instrument because of potentially spotty internet service.

Furthermore, the online and live Code Next student experiences vary in ways that may have affected survey outcomes. While online students engage in club programming for an average of 2.5 hours per week, live students have the opportunity to take multiple clubs and Saturday programming, meaning they can spend up to six or seven hours in the lab each week (if they so choose). The labs are open every day Tuesday through Saturday as well for students to access, and some live students take advantage of the open-door policy to come grab snacks, study, and generally spend time talking with staff. The online students do not have this luxury, as they are only able to take one 2-hour club per week and occasionally participate in Office Hours with Code Next coaches.

Additionally, the three in-person lab datasets may have had some variance given the differences in lab-specific experiences. When the survey was administered, the Code Next Detroit lab had only been open for three months; comparatively, the Code Next Oakland and Code Next New York labs opened in 2016. While the Code Next Detroit lab only services a founding class of 46 students as of spring 2023, the other live labs each have more than 150 students, as well as larger and more robust collections of curriculum, technical devices and Google coaches. In addition, some of the Code Next Oakland and Code Next New York students have been in the program for more than the 2022-2023 year, thus giving them more opportunity to develop tech social capital. This variance in access, time and resources thus may have affected the outcomes from the “in-person” student sample set.

A few last limitations relate to the design of the research, its connection to time constraints brought about by the sample site's programming schedule, and issues with causal inferences. Code Next operates on a seasonal, four-quarter academic schedule, with each quarter running for nine weeks. Ideally, students would have been able to complete the pre-program portion of the survey prior to the start of the academic year (fall quarter), rather than having to recall their experiences in response to survey questions that began with "Before you started in Code Next." However, that would have required waiting an additional six months from the date of the survey adaptation, and the constraints of this dissertation process rendered that impossible.

Implications for Stakeholders

Education Researchers

This research provided a number of implications and possibilities for future study for education researchers. First, while this survey was by no means perfect or externally-validated, it provided an exploratory first attempt at measuring tech social capital and adapting existing indices. Though there are still many debates around how to measure social capital, as was explored in Chapter 2, this study provided one possibility for how to borrow indices from other research industries, like public health and sociology, and modify them given the specific sample or environment.

Second, even though more validation needs to be done on the survey instrument, this study provided an example of how to adapt social capital indices for content areas other than computer science education. While this study focuses exclusively on computer science education and its connection to technical workforce development, this approach is flexible enough that a researcher could, for example, generate an arts-relevant social capital index for studying artistic workforce development.

Third, this study provides an example of examining social capital through a community cultural wealth lens as an overall orienting lens (Creswell & Creswell, 2018). A major source of pride in this study was the inclusion of Black and Latino/Hispanic student voices and perceptions in the methodological approach. I hope that education researchers consider integrating student voices more consistently and fruitfully, as the lack of student voice is dismally apparent amongst existing scholarship and reinforces that insidiously deficit mindset.

K-16 Educators

In the metrics-driven world of education, assessments are a constant. And yet, despite this omnipresent focus on measurement, we rarely see that approach applied to anything beyond students' content knowledge. Thus, my hope is that this research supports K-16 computer science educators in a few different ways.

First, this study hopefully illustrates that educators and other stakeholders in learning environments possess a deep responsibility to students—especially students of color—to develop and measure their tech social capital as thoroughly as hard computational skills. While the tech workforce does search for the best and the brightest, many companies put a major stake on talent referrals (Chua & Mazmanian, 2020), and that model does not appear to be changing any time soon. There are various tactics for developing social capital with Black and Latino/Hispanic populations, some of which are described in research referenced in this dissertation (Kahne & Bailey, 1999; Glaeser, 200l; Jarrett, Sullivan, & Watkins, 2005; Farmer-Hinton, 2008; Stanton-Salazar, 2011; Galindo and Abel, 2017). Galindo and Abel's case study of a full-service community school, for example, provides descriptions of how principals, teachers, and staff can develop stronger and longer-lasting relationships with students. For informal educators, case studies like that of Kahne and Bailey focus on tactics aligned to types of social capital, such as how “I Have a Dream” programs emphasized mentorship programming to bolster “social trust”. Anyone who works with students bears responsibility for helping them to grow their networks, and this includes any and all stakeholders in education spaces.

Second, this study provides a first-step at encouraging computer science educators and administrators, including the staff at Code Next, to measure social capital as thoroughly as content knowledge. Just as with researchers, this approach to social capital measurement translates into other subject areas beyond computer science. It is time for us to study and attempt to measure social capital as thoroughly and consistently as we do content knowledge with exams like the SAT or STAAR. But for now, my hope is that any and all educators who touch computer science in some way—including testing administrators—consider applying this approach to their assessment strategy.

Third, I hope that this research pushes K-16 educators to challenge the deficit mindset that so commonly plagues conversations around Black and Latino/Hispanic students. I encourage educators to get a better understanding of how to work with families in encouraging computing by consulting tools from organizations like the National Center for Women & Information Technology (NCWIT) and the Association for Computing Machinery (ACM). Both organizations have conducted research around this topic (DuBow, Farmer, Wu & Fredrickson, 2013; Clarke-Midura et al, 2019) and have toolkits on their websites.

Technical Workforce and Corporations

I was largely inspired to conduct this research because of conversations I have had with colleagues at large technical organizations like Google, Microsoft, and Apple. Many of these organizations run programs intended to reach young computer science learners. However, I often hear a problematic assumption.

Some subscribe to the "meritocracy argument"—that anyone can get into the Google's and Apple's of the world if they work hard enough and develop strong coding skills. However, a major (and supposedly "optional") component of the Big Tech application process is acquiring a "referral" from an existing employee (Chua & Mazmanian, 2020), which is intricately related to one's social capital. Both Pierre Bourdieu (1986) and Robert Putnam (2000) alluded to the "old boys' network," describing the hidden power structures that networks create within organizations. Since then, many researchers have described the "glass ceiling" and "structural limitations" hindering marginalized communities from accessing those networks (Cech & Blair-Loy, 2010). This Big Tech referral system is a key part of that. This dissertation research suggests that social capital is a concept to be recognized, acknowledged, and further studied. Thus, I have two hopes. First, I hope that individuals working in human resources and recruitment at Big Tech corporations take the realities of "tech social capital" to heart, and consider reworking their limiting referral structures. Second, I hope that individuals that run corporate social responsibility programs for computer science learners, from programs like Code Next to online training portals, begin to place more emphasis on social capital development.

Suggestions for Future Research

Given the limitations I listed above, there is ample opportunity for both myself and other researchers to take this study further and identify opportunities for different sample sites and longer longitudinal studies.

First, I would like to refine, test, and validate the measures derived from the survey. This was truly an "exploratory" study—a first step into creating a valid instrument for measuring social capital development and exploring comparisons between live and online students. By including both RQ2 and RQ2a as foci for the research design, I covered more ground and generated more hypotheses; however, there is now need for a validation study to measure this survey's potential to evaluate program outcomes.

Following, I'd like to see this research replicated, but amongst different afterschool programs and with larger groups of students. It would also be ideal to assess change longitudinally through surveys administered before and after program participation, as opposed to a retrospective model.

Additionally, I would like to see more research with larger sample sizes comparing online and in-person student experiences, ideally where the same program offers curriculum in those two different modalities. Some individuals in the tech sectors believe that online programs support students as much as live programs, and because online programs are often cheaper and easier to scale, they are worth more investment. Thus, we possess a huge need for research to test whether those assumptions are true.

I also believe that this study should be redone with an intersectional approach to analysis. If I had more time and a larger sample, I would have compared PTSC scores with an intersectional lens—looking at how race, class, gender, and other individual characteristics "intersect" and manifest in the scores, as Kimberlee Crenshaw described in her seminal research (1988).

Dissemination

As mentioned before, this study was exploratory in nature. As such, prior to disseminating the content, I first need to engage in more refinement, piloting, and validating. I will then implement it within the Code Next and larger Google communities. Eventually, the Code Next team plans to conduct this survey on an annual basis, attempting to capture every student in the program. Google has a number of other computer science programs aimed at supporting Black and Latino/Hispanic students, such as its Tech Exchange partnership with Historically Black Colleges and Universities (HBCUs) and Hispanic-Serving Institutions (HSIs). I will share this research with Google programs like Tech Exchange as a possible tool. I also plan on entering this dissertation into Google's internal research database, making it available for all future Google staff members.

On a more macro level, I plan on applying to and presenting this information at various conferences. Thus far, I have been invited to present this research at computer science education practitioner conferences like Los Angeles Unified School District's #CS4LAUSD conference, but I also plan on applying to present at the next AERA (American Educational Research Association) Conference in July 2024.

And lastly, I plan to continue my exploration into social capital theory and research, engaging in deeper study of social capital measurements. I hope to partner with organizations like the Search Institute or the Christensen Institute, who have both made great strides in the study of social capital measurement and increasing students' ability to mobilize social capital. Lastly, given my interests in comparing live and online social capital development, I hope to partner with organizations conducting online social network analysis (SNA) to provide insights and potentially inspire more studies of live vs. online education environments.

Final Thoughts: Reflection

The world of tech is a homogenous place. When I walk onto the Google campus in Mountain View, I see it. We live in a world where who you know can matter, but also where systems of power benefit those with certain networks and access to resources. As Bourdieu described early on, social capital can be used for both positive and negative purposes. Those with social capital may wield it to maintain power and reinforce authority, often at the expense of those with less. For young people of color, we owe it to them to provide them with just as many mechanisms for social capital development as we do knowledge and skill attainment, both through providing opportunities for growth and by validating their lived experiences. Otherwise, we do them a disservice—we continue the vicious cycle of inequitable workforce development and generational wealth distribution, all under the meritocracy guise. There is so much more opportunity for exploration—for researchers, for educators, for tech companies, and, of course, for the students. I pray that this dissertation serves as just one small, exploratory step on that burgeoning path forward.

Appendix

Appendix A: Qualitative Analysis Codes

"Relationships" Descriptive Codes	**Sub-Codes**	**Sample from Qualitative Data**
Adults: Family	Parents	"I guess, just my mom. She brought me into the program."
	Grandparents	"I didn't mention that my grandparents invested in me physically. Like I have a great monitor setup."
	Non-nuclear relatives (uncles, godparents, etc.)	"One of my aunts is also in computer science."
	Family friends (18+)	"They're just an old family friend and they kind of… They were in the software developing field for a while."
Adults: Formal school	Librarians	"So the librarian, she and I would go in…"
	Teachers	"I call him Jorge, but his name is Mr. Gonzalez and was such a great teacher."
Adults: Non-familial, non-formal spaces	Afterschool program teachers or administrators	"I was in a program, and there's a coding coach who goes by Bradley."
	Other	"My mom's boss. He's trying to help me a lot."
Peers: Family	Siblings	"My brother, he really likes computer science too."
	Non-nuclear relatives (cousins, etc.)	"My cousin Ricky. Because he's always… In my feeling, he's like my role model."
	Family friends (up to 18)	"Mainly just outside friends, like friends, like family friends."
Peers: Formal school	Classmates from STEM classes	"So there's one friend of mine, who is in my computer science classes, both years."
	General friends from school	"My best friend Julio… Even though he's straight so far away from, like, my interests and stuff, he still keeps that same passion that I have."
Peers: Non-familial,	Peers from church	"...a lot of my peers that go to my church. They have definitely, like, prayed over me."

non-formal spaces		
	Peers from afterschool programs	"In the lab, there was girls that, like, taught me how to code."
	Peers from sports	"Someone on my sports team, he was talking about building a new computer to write code."
	Other	"I've met some other game developers, they're a little bit older than me though."

"Resources" Descriptive Codes	**Sub-Codes**	**Sample from Qualitative Data**
Resources connected to through adults	Introduction to programs	"They actually let us know about the opportunity at Google, which is Connect."
	Links/helpful information re: content	"She'll give us a simulation where a computer is messed up and we have to figure it out."
	Relationships/connections	"She brought me, [and] I got to meet mostly people in robotics."
	Access to software	"He even let me keep, like, my Adobe subscription."
	Access to tech/hardware	"Like, if we were learning how to do HTML, they would give us computers."
	Tutoring	"He's the one who gave me ACE mentoring."
	Money or paid for student	"My grandfather definitely contributed by, like, a little money here and there."
	Other	"He's showing me a few different colleges."
Resources connected to through peers	Introduction to programs	"Yeah, he was the one that introduced me to Robotics Club at my high school now."
	Links/helpful information re: content	"Usually, when I have a question, he'll send me a video explaining it."
	Relationships/connections	"She goes to Stony Brook, which is like a college or university around here… She's trying to connect me to the computer science program over there."

	Access to software	“He showed me a software application that made it really easy.”
	Access to tech/hardware	“Sometimes he’ll hand me, like, things, certain cables that I might need to work with stuff or any computer part that I might need.”
	Tutoring	“My cousins, they would give me advice. Like, give me little tips on how to fix my code or how to check on it.”
	Other	“She really just provided me with a lot of support and just, you know, like, confidence.”

Appendix B: Interview Questions

Good afternoon, and thank you for taking the time to be interviewed! The data that comes from this interview will help me better understand how high school students think about their networks and relationships.

This interview will last approximately 45 minutes. I am using a screen/audio recorder so I can be more attentive to your responses instead of taking notes. Your answers will be kept confidential, and I will be using a pseudonym for you in my report. If at any time you would like me to turn off the recorder, please let me know.

I'll send you the responses afterwards to make sure they are accurate and represent your answers well. As a thank you, you will be compensated $10 for your participation.

Do you have any questions before we start the interview? Great, let's begin.

PART ONE: RELATIONSHIP BUILDING WITH ADULTS

For this first part, I'm going to ask you about your background in computer science and the role played by the adults in your life.

1. Tell me about how you got interested in computer science.
2. Are there any adults in your life that encouraged you or helped you get into computer science? *(Definition: "Computer science" includes coding, working with software, and working with computers or other hardware like laser-cutters or 3-D printers.)*
   [PROBE FOR: FAMILY, FORMAL SCHOOL, OUTSIDE OF FORMAL SCHOOL]
   a. Tell me more about how they encouraged or helped you.
   b. [OPTIONAL] How did that connection / those connections come to form?
   c. [OPTIONAL] How is that connection / are those connections important to you? Tell me more.
3. Tell me about any of those adults who connected you with resources related to helping you learn computer science. What resources did they give you or you with? *(Definition: "Resources" can be tech, or money, or access to software, or tutoring, or help from peers.)*
   [PROBES: MONEY, TECH, ACCESS TO SOFTWARE/HARDWARE, CONNECTIONS THEY HAVE, KNOWLEDGE]
4. In what ways do your relationships with adults affect your thoughts about working in the computer science field in the future, if at all?

PART TWO: RELATIONSHIP BUILDING WITH PEERS

For this second part, I'm going to ask you about the different relationships you have with peers, or people your age.

5. Are there any peers in your life who encouraged you or helped you get into computer science? *(Definition: "Computer science" includes coding, working with software, and working with computers or other hardware like laser-cutters or 3-D printers.)* [PROBE FOR: FAMILY, FORMAL SCHOOL, OUTSIDE OF FORMAL SCHOOL]
    a. Tell me more about how they encouraged or helped you.
    b. [OPTIONAL] How did that connection / those connections come to form?
    c. [OPTIONAL] How is that connection / are those connections important to you? Tell me more.
6. Tell me about any of those peers who connected you with resources related to helping you learn computer science. What resources did they give you or you with? *(Definition: "Resources" can be tech, or money, or access to software, or tutoring, or help from peers.)* [PROBES: MONEY, TECH, ACCESS TO SOFTWARE/HARDWARE, CONNECTIONS THEY HAVE, KNOWLEDGE]
7. In what ways do your relationships with peers affect your thoughts about working in the computer science field in the future, if at all?

8. Are there any other relationships with adults or peers that got you into computer science—ones you didn't mention before that you'd like to discuss before we end?

I have learned so much from this interview. Thank you so much for your time.

Appendix C: Survey (Google Docs version)

Directions: Please fill out the following survey to the best of your abilities.

Part 1:
Please label the number that best describes your answer to each of the following questions. This section describes the time before you were in Code Next.

	Pick a number for each category			
Bo1: ***Before you started in Code Next,*** among the people in each of the following six categories, how many did you *regularly talk with about computer science*? *(Definition: "Computer science" includes coding, working with software, and working with computers or other hardware like laser-cutters or 3-D printers.)* Parents/guardians Siblings Extended family (aunts, uncles, grandparents, cousins etc.) Family friends Teacher/coaches from school Teacher/coaches from outside of school Friends from school Friends from outside of school	**No one** **X** **X** **X** **X** **X** **X** **X** **X**	**1 person** **X** **X** **X** **X** **X** **X** **X** **X**	**2 to 3 people** **X** **X** **X** **X** **X** **X** **X** **X**	**4 or More** **X** **X** **X** **X** **X** **X** **X** **X**
Bo2: ***Before you started in Code Next,*** among the people in each of the following six categories, how many *did you trust enough to talk with about computer science?* *(Definition: "Computer science" includes coding, working with software, and working with computers or other hardware like laser-cutters or 3-D printers.)* *(Definition: "Trust" describes feeling comfortable, open with, or like you can depend on someone.)*	**No one** **X**	**1 person** **X**	**2 to 3 people** **X**	**4 or More** **X**

Parents/guardians Siblings Extended family (aunts, uncles, grandparents, cousins etc.) Family friends Teacher/coaches from school Teacher/coaches from outside of school Friends from school Friends from outside of school	**X** **X** **X** **X** **X** **X** **X**	**X** **X** **X** **X** **X** **X** **X**	**X** **X** **X** **X** **X** **X** **X**	**X** **X** **X** **X** **X** **X** **X**
Bo3: ***Before you started in Code Next,*** among people in each of the following six categories, how many of them *helped you if you needed support in coding or doing tech projects?* Parents/guardians Siblings Extended family (aunts, uncles, grandparents, cousins etc.) Family friends Teacher/coaches from school Teacher/coaches from outside of school Friends from school Friends from outside of school	**No one** **X** **X** **X** **X** **X** **X** **X** **X**	**1 person** **X** **X** **X** **X** **X** **X** **X** **X**	**2 to 3 people** **X** **X** **X** **X** **X** **X** **X** **X**	**4 or More** **X** **X** **X** **X** **X** **X** **X** **X**
Br1: ***Before you started in Code Next,*** of all of the people you thought of above, how many of them *possess the following resources?* ~Technology or hardware ~Software ~Relationships or connections to people in tech ~Willingness to provide you encouragement or moral support ~Links to helpful information or websites ~Money ~Knowledge of computer science programs or opportunities ~Expertise or the ability to tutor you	**No one** **X** **X** **X** **X** **X** **X** **X** **X**	**1 person** **X** **X** **X** **X** **X** **X** **X** **X**	**2 to 3 people** **X** **X** **X** **X** **X** **X** **X** **X**	**4 or More** **X** **X** **X** **X** **X** **X** **X** **X**
Br2: ***Before you started in Code***	**No one**	**1 person**	**2 to 3 people**	**4 or More**

Next, of all of the people you thought of above, how many of them *connected you to or helped you get the following resources?* ~Technology or hardware ~Software ~Relationships or connections to people in tech ~Willingness to provide you encouragement or moral support ~Links to helpful information or websites ~Money ~Knowledge of computer science programs or opportunities ~Expertise or the ability to tutor you	**X** **X** **X** **X** **X** **X** **X** **X**	**X** **X** **X** **X** **X** **X** **X** **X**	**X** **X** **X** **X** **X** **X** **X** **X**	**X** **X** **X** **X** **X** **X** **X** **X**
Br3: ***Before you started in Code Next,*** of all the people you thought about above, how many of them did you think *could help you in the future to access the following resources*? ~Technology or hardware ~Software ~Relationships or connections to people in tech ~Willingness to provide you encouragement or moral support ~Links to helpful information or websites ~Money ~Knowledge of computer science programs or opportunities ~Expertise or the ability to tutor you	**No one** **X** **X** **X** **X** **X** **X** **X** **X**	**1 person** **X** **X** **X** **X** **X** **X** **X** **X**	**2 to 3 people** **X** **X** **X** **X** **X** **X** **X** **X**	**4 or More** **X** **X** **X** **X** **X** **X** **X** **X**

Part 2:
Please label the number that best describes your answer to each of the following questions. This section now, since you've been in Code Next.

	Pick a number for each category

Bo1: ***Currently,*** among the people in each of the following six categories, how many do you *regularly talk with about computer science*? *(Definition: "Computer science" includes coding, working with software, and working with computers or other hardware like laser-cutters or 3-D printers.)* Parents/guardians Siblings Extended family (aunts, uncles, grandparents, cousins etc.) Family friends Teacher/coaches from school Teacher/coaches from outside of school Friends from school Friends from outside of school	**No one** **X** **X** **X** **X** **X** **X** **X** **X**	**1 person** **X** **X** **X** **X** **X** **X** **X** **X**	**2 to 3 people** **X** **X** **X** **X** **X** **X** **X** **X**	**4 or More** **X** **X** **X** **X** **X** **X** **X** **X**
Bo2: ***Currently,*** among the people in each of the following six categories, how many do you *trust enough to talk with about computer science?* *(Definition: "Computer science" includes coding, working with software, and working with computers or other hardware like laser-cutters or 3-D printers.)* *(Definition: "Trust" describes feeling comfortable, open with, or like you can depend on someone.)* Parents/guardians Siblings Extended family (aunts, uncles, grandparents, cousins etc.) Family friends Teacher/coaches from school Teacher/coaches from outside of school Friends from school Friends from outside of school	**No one** **X** **X** **X** **X** **X** **X** **X** **X**	**1 person** **X** **X** **X** **X** **X** **X** **X** **X**	**2 to 3 people** **X** **X** **X** **X** **X** **X** **X** **X**	**4 or More** **X** **X** **X** **X** **X** **X** **X** **X**
Bo3: ***Currently,*** among people in each of the following six categories,	**No one**	**1 person**	**2 to 3 people**	**4 or More**

how many of them *help you if you need support in coding or doing tech projects?* Parents/guardians Siblings Extended family (aunts, uncles, grandparents, cousins etc.) Family friends Teacher/coaches from school Teacher/coaches from outside of school Friends from school Friends from outside of school	 **X** **X** **X** **X** **X** **X** **X** **X**	 **X** **X** **X** **X** **X** **X** **X** **X**	 **X** **X** **X** **X** **X** **X** **X** **X**	 **X** **X** **X** **X** **X** **X** **X** **X**
Br1: ***Currently,*** of all the people you thought about above, how many of them *possess the following resources*? ~Technology or hardware ~Software ~Relationships or connections to people in tech ~Willingness to provide you encouragement or moral support ~Links to helpful information or websites ~Money ~Knowledge of computer science programs or opportunities ~Expertise or the ability to tutor you	**No one** **X** **X** **X** **X** **X** **X** **X** **X**	**1 person** **X** **X** **X** **X** **X** **X** **X** **X**	**2 to 3 people** **X** **X** **X** **X** **X** **X** **X** **X**	**4 or More** **X** **X** **X** **X** **X** **X** **X** **X**
Br2: ***Currently,*** of all the people you thought about above, how many of them *have given you or helped you get the following resources*? ~Technology or hardware ~Software ~Relationships or connections to people in tech ~Willingness to provide you encouragement or moral support ~Links to helpful information or websites ~Money ~Knowledge of computer science programs or opportunities ~Expertise or the ability to tutor you	**No one** **X** **X** **X** **X** **X** **X** **X** **X**	**1 person** **X** **X** **X** **X** **X** **X** **X** **X**	**2 to 3 people** **X** **X** **X** **X** **X** **X** **X** **X**	**4 or More** **X** **X** **X** **X** **X** **X** **X** **X**
Br3: ***Currently,*** of all the people you	**No one**	**1 person**	**2 to 3 people**	**4 or More**

thought about above, how many of them *will you go to in the future for the following resources*? ~Technology or hardware ~Software ~Relationships or connections to people in tech ~Willingness to provide you encouragement or moral support ~Links to helpful information or websites ~Money ~Knowledge of computer science programs or opportunities ~Expertise or the ability to tutor you	 **X** **X** **X** **X** **X** **X** **X** **X**	 **X** **X** **X** **X** **X** **X** **X** **X**	 **X** **X** **X** **X** **X** **X** **X** **X**	 **X** **X** **X** **X** **X** **X** **X** **X**

Part 3: Please answer the following demographic questions.

1. What grade level are you in?
   a. Freshman in high school
   b. Sophomore in high school
   c. Junior in high school
   d. Senior in high school

2. What is your gender?
   a. Male
   b. Female
   c. Non-binary / other gender
   d. Prefer not to answer

3. I identify as... (Please select all that apply.)
   a. White
   b. Black
   c. Latino/Hispanic
   d. Asian
   e. Native or Indigenous
   f. Native Hawaiian or Pacific Islander
   g. Other/Unknown
   h. Prefer not to say

4. What Code Next lab are you in?
   a. Oakland, CA
   b. Detroit, MI
   c. New York City, NY
   d. Online (Connect)

i. Where in the United States? ___________

5. If you are interested in being entered into the raffle, what is your preferred email address [OPTIONAL]? Your name will be separated from the results.

<u>Appendix D: Survey (Qualtrics version)</u>

Webpage 1

UCLA GRADUATE SCHOOL OF
EDUCATION & INFORMATION STUDIES

On the following page, please label the number that best describes your answer to each of the following questions.

This section describes the time BEFORE you were in Code Next.

→

Webpage 2

UCLA GRADUATE SCHOOL OF
EDUCATION & INFORMATION STUDIES

Before you started in Code Next, among the people in each of the following six categories, ***how many did you regularly talk with about computer science?***

(Definition: “Computer science” includes coding, working with software, and working with computers or other hardware like laser-cutters or 3-D printers.)

	No one	1 person	2 to 3 people	4 or more people
Parents/guardians	○	○	○	○
Siblings	○	○	○	○
Extended family (aunts, uncles, grandparents, cousins etc.)	○	○	○	○
Family friends	○	○	○	○
Teacher/coaches from school	○	○	○	○
Teacher/coaches from outside of school	○	○	○	○
Friends from school	○	○	○	○
Friends from outside of school	○	○	○	○

Before you started in Code Next, among the people in each of the following six categories, ***how many do you trust enough to talk with about computer science***?

(Definition: "Computer science" includes coding, working with software, and working with computers or other hardware like laser-cutters or 3-D printers.)
(Definition: "Trust" describes feeling comfortable, open with, or like you can depend on someone.)

	No one	1 person	2 to 3 people	4 or more people
Parents/guardians	○	○	○	○
Siblings	○	○	○	○
Extended family (aunts, uncles, grandparents, cousins etc.)	○	○	○	○
Family friends	○	○	○	○
Teacher/coaches from school	○	○	○	○
Teacher/coaches from outside of school	○	○	○	○
Friends from school	○	○	○	○
Friends from outside of school	○	○	○	○

Before you started in Code Next, among people in each of the following six categories, ***how many of them helped you if you needed support in coding or doing tech projects***?

	No one	1 person	2 to 3 people	4 or more people
Parents/guardians	○	○	○	○
Siblings	○	○	○	○
Extended family (aunts, uncles, grandparents, cousins etc.)	○	○	○	○
Family friends	○	○	○	○
Teacher/coaches from school	○	○	○	○
Teacher/coaches from outside of school	○	○	○	○
Friends from school	○	○	○	○
Friends from outside of school	○	○	○	○

Before you started in Code Next, of all of the people you thought of above, ***how many of them possess the following resources***?

	No one	1 person	2 to 3 people	4 or more people
Technology or hardware	○	○	○	○
Software	○	○	○	○
Relationships or connections to people in tech	○	○	○	○
Willingness to provide you encouragement or moral support	○	○	○	○
Links to helpful information or websites	○	○	○	○
Money	○	○	○	○
Knowledge of computer science programs or opportunities	○	○	○	○
Expertise or the ability to tutor you	○	○	○	○

Before you started in Code Next, of all of the people you thought of above, ***how many of them connected you to or helped you get the following resources***?

	No one	1 person	2 to 3 people	4 or more people
Technology or hardware	○	○	○	○
Software	○	○	○	○
Relationships or connections to people in tech	○	○	○	○
Willingness to provide you encouragement or moral support	○	○	○	○
Links to helpful information or websites	○	○	○	○
Money	○	○	○	○
Knowledge of computer science programs or opportunities	○	○	○	○
Expertise or the ability to tutor you	○	○	○	○

Before you started in Code Next, of all the people you thought about above, ***how many of them did you think could help you in the future to access the following resources?***

	No one	1 person	2 to 3 people	4 or more people
Technology or hardware	○	○	○	○
Software	○	○	○	○
Relationships or connections to people in tech	○	○	○	○
Willingness to provide you encouragement or moral support	○	○	○	○
Links to helpful information or websites	○	○	○	○
Money	○	○	○	○
Knowledge of computer science programs or opportunities	○	○	○	○
Expertise or the ability to tutor you	○	○	○	○

→

Webpage 3

UCLA GRADUATE SCHOOL OF EDUCATION & INFORMATION STUDIES

On the next page, please label the number that best describes your answer to each of the following questions.

This section describes your CURRENT situation, right now in March 2023.

→

Webpage 4

UCLA GRADUATE SCHOOL OF EDUCATION & INFORMATION STUDIES

CURRENTLY, among the people in each of the following six categories, ***how many do you regularly talk with about computer science?***

(Definition: "Computer science" includes coding, working with software, and working with computers or other hardware like laser-cutters or 3-D printers.)

	No one	1 person	2 to 3 people	4 or more people
Parents/guardians	○	○	○	○
Siblings	○	○	○	○
Extended family (aunts, uncles, grandparents, cousins etc.)	○	○	○	○
Family friends	○	○	○	○
Teacher/coaches from school	○	○	○	○
Teacher/coaches from outside of school	○	○	○	○
Friends from school	○	○	○	○
Friends from outside of school	○	○	○	○

CURRENTLY, among the people in each of the following six categories, ***how many do you trust enough to talk with about computer science***?

(Definition: "Computer science" includes coding, working with software, and working with computers or other hardware like laser-cutters or 3-D printers.)
(Definition: "Trust" describes feeling comfortable, open with, or like you can depend on someone.)

	No one	1 person	2 to 3 people	4 or more people
Parents/guardians	○	○	○	○
Siblings	○	○	○	○
Extended family (aunts, uncles, grandparents, cousins etc.)	○	○	○	○
Family friends	○	○	○	○
Teacher/coaches from school	○	○	○	○
Teacher/coaches from outside of school	○	○	○	○
Friends from school	○	○	○	○
Friends from outside of school	○	○	○	○

CURRENTLY, among people in each of the following six categories, ***how many of them help you if you need support in coding or doing tech projects***?

	No one	1 person	2 to 3 people	4 or more people
Parents/guardians	◯	◯	◯	◯
Siblings	◯	◯	◯	◯
Extended family (aunts, uncles, grandparents, cousins etc.)	◯	◯	◯	◯
Family friends	◯	◯	◯	◯
Teacher/coaches from school	◯	◯	◯	◯
Teacher/coaches from outside of school	◯	◯	◯	◯
Friends from school	◯	◯	◯	◯
Friends from outside of school	◯	◯	◯	◯

CURRENTLY, of all of the people you thought of above, ***how many of them possess the following resources***?

	No one	1 person	2 to 3 people	4 or more people
Technology or hardware	◯	◯	◯	◯
Software	◯	◯	◯	◯
Relationships or connections to people in tech	◯	◯	◯	◯
Willingness to provide you encouragement or moral support	◯	◯	◯	◯
Links to helpful information or websites	◯	◯	◯	◯
Money	◯	◯	◯	◯
Knowledge of computer science programs or opportunities	◯	◯	◯	◯
Expertise or the ability to tutor you	◯	◯	◯	◯

CURRENTLY, of all of the people you thought of above, ***how many of them have given you or helped you get the following resources?***

	No one	1 person	2 to 3 people	4 or more people
Technology or hardware	◯	◯	◯	◯
Software	◯	◯	◯	◯
Relationships or connections to people in tech	◯	◯	◯	◯
Willingness to provide you encouragement or moral support	◯	◯	◯	◯
Links to helpful information or websites	◯	◯	◯	◯
Money	◯	◯	◯	◯
Knowledge of computer science programs or opportunities	◯	◯	◯	◯
Expertise or the ability to tutor you	◯	◯	◯	◯

CURRENTLY, of all of the people you thought of above, ***how many of them will you go to in the future for the following resources?***

	No one	1 person	2 to 3 people	4 or more people
Technology or hardware	○	○	○	○
Software	○	○	○	○
Relationships or connections to people in tech	○	○	○	○
Willingness to provide you encouragement or moral support	○	○	○	○
Links to helpful information or websites	○	○	○	○
Money	○	○	○	○
Knowledge of computer science programs or opportunities	○	○	○	○
Expertise or the ability to tutor you	○	○	○	○

→

Webpage 5

UCLA GRADUATE SCHOOL OF EDUCATION & INFORMATION STUDIES

What grade level are you in?

- ○ Freshman in high school
- ○ Sophomore in high school
- ○ Junior in high school
- ○ Senior in high school

What is your gender?

- ○ Male
- ○ Female
- ○ Non-binary / other gender
- ○ Prefer not to say

I identify as... (Please select all that apply.)

- ○ White
- ○ Black
- ○ Latino/Hispanic
- ○ Asian
- ○ Native or Indigenous
- ○ Native Hawaiian or Pacific Islander
- ○ Other/Unknown
- ○ Prefer not to say

What Code Next lab are you in?

- ○ Oakland, CA
- ○ Detroit, MI
- ○ New York City, NY
- ○ Online (Connect) - Where in the United States?

If you are interested in being entered into the raffle, what is your preferred email address [OPTIONAL]? Your name will be separated from the results.

→

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