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Rewriting the Script for Equity-Minded Graduate School Pathways:  
Examining Mechanisms of Mentoring and Psychosocial Development in Computing Disciplines

A dissertation submitted in partial satisfaction of the requirements for the degree  
Doctor of Philosophy in Education

by

Ann Marie Wofford

2021

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## ABSTRACT OF THE DISSERTATION

Rewriting the Script for Equity-Minded Graduate School Pathways:  
Examining Mechanisms of Mentoring and Psychosocial Development in Computing Disciplines

by

Ann Marie Wofford

Doctor of Philosophy in Education

University of California, Los Angeles, 2021

Professor Linda J. Sax, Chair

Tensions between enrollment growth, faculty shortages, and persistent inequity characterize the current landscape of postsecondary computing education. As individuals who pursue graduate studies in computing are likely future leaders in the tech industry and academic computing spaces, colleges and universities need to restructure mechanisms of support for graduate school pathways in the field. Structured across three articles, I interrogate how collegiate computing environments may contribute to disparities in the psychosocial development and mentoring relationships of undergraduates who aspire to earn a computing graduate degree. The first article uses quantitative longitudinal data to examine the direct and indirect predictors of students' self-confidence for computing graduate school admission, focusing on the role of introductory computing courses as well as computing self-efficacy and identity among 349 computing graduate aspirants. The second study uses critical quantitative

approaches with a more nuanced sample from the same longitudinal dataset to investigate how power within computing departments shapes the nature of mentorship that 442 graduate aspirants receive and how such mentoring relationships may inequitably contribute to students' computing self-efficacy and computing identity. The third study qualitatively explores one particular type of mentorship that graduate aspirants may have, centering on how 10 current graduate students in informatics make meaning of serving as “stage-ahead” mentors to undergraduate students in computing and how mentors' approaches may be reflective of and shaped by the social identities of mentors and mentees as well as the organizational context.

Collectively, these three studies expand what is known about computing graduate pathways and mentoring relationships in computing in two primary ways. First, findings document some of the salient inequities that characterize the stages between graduate aspiration and matriculation. Second, findings explore how different mentors in computing departments may face varying affordances or constraints in providing equity-minded guidance based on their positional power within the institution. These studies may be of particular interest to academic leaders and policymakers in collegiate computing spaces, as institutional changes to the opportunity, value, and rewards associated with mentoring and psychosocial support will be crucial to disrupt the minoritization and disparities that perpetuate students' educational trajectories in computing.

The dissertation of Ann Marie Wofford is approved.

Kimberley Gomez

Kimberly A. Griffin

Sylvia Hurtado

Linda J. Sax, Committee Chair

University of California, Los Angeles

2021

## DEDICATION

*To my parents, Dave and Gwen Lewis-Jones, who are emblems of hard work, humility, and compassion, and to my greenhouse of mentors—without whom my curiosity and passion would have fallen short of full bloom.*

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### CHAPTER 2

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I am quite certain that, whenever I come up against a challenging problem, my internal dialogue will always whisper my mom and dad’s encouragement of “do your best.” I heard this phrase regularly as I sat at the kitchen table—not at the desk in my bedroom, often to my parents’ chagrin—with my head in books and a slew of colorful pens that I curated for my notetaking. My parents likely thought that this phrase was a way to support my resilience through perplexing homework problems without pressuring me to excel. Perhaps they knew that their daughter’s nature and love of learning didn’t require it; because, to me, “do your best” always inspired me to keep striving. I knew that, with the best I did at the moment, I could always challenge my knowledge to go one step further. For this lesson, models of public service careers, and boundless love and support, I am forever grateful.

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work with those in the higher education community and imagining all of the directions that this research can go in the future.

## VITA

### Education

---

- 2013 Bachelor of Science in Education, Social Studies, Minor in International Studies  
University of Central Missouri, Warrensburg, MO
- 2015 Master of Arts, Educational Administration  
University of Missouri – Kansas City, Kansas City, MO
- 2018 Master of Arts, Education (Higher Education and Organizational Change)  
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### Experience and Awards

---

- 2013 – 2015 Coordinator of Admissions and Recruitment  
University of Missouri – Kansas City School of Medicine, Kansas City, MO
- 2015 – 2017 Admissions Coordinator for Graduate Programs  
University of Missouri – Kansas City School of Medicine, Kansas City, MO
- 2017 – 2021 Research Analyst, *Momentum: Accelerating Equity in Computing & Technology*  
University of California, Los Angeles, Los Angeles, CA
- 2017 – Research Affiliate, Trajectories of Early Career Research  
Utah State University, Logan, UT
- 2018 Graduate Summer Research Mentorship Fellowship, Graduate Division (\$6,000)  
University of California, Los Angeles, Los Angeles, CA
- 2019 Philip N. Clark Award, Higher Education and Organizational Change  
University of California, Los Angeles, Los Angeles, CA
- 2020 – 2021 Graduate Research Mentorship Fellowship, Graduate Division (\$20,000)  
University of California, Los Angeles, Los Angeles, CA
- 2020 – 2021 P.E.O. Scholar Award (\$15,000)  
International Chapter of the P.E.O. Sisterhood
- 2020 – 2022 ACPA Foundation Grant, Co-Principal Investigator (\$2,500)  
ACPA—College Student Educators International
- 2021 – 2022 AERA Division D Research Grant, Co-Principal Investigator (\$5,000)  
American Educational Research Association
- 2021 – Research Affiliate, The Inclusive Graduate Education Network Research Hub  
University of Southern California, Los Angeles, CA

**Wofford, A. M.,** & Blaney, J. M. (2021). (Re)Shaping the socialization of scientific labs: Understanding women's doctoral experiences in STEM lab rotations. *The Review of Higher Education*, 44(3), 357-386. <https://doi.org/10.1353/rhe.2021.0001>

**Wofford, A. M.,** Griffin, K. A., & Roksa, J. (2021). Unequal expectations: First-generation and continuing-generation students' anticipated relationships with doctoral advisors in STEM. *Higher Education*. Advance online publication. <https://doi.org/10.1007/s10734-021-00713-8>

**Wofford, A. M.** (2021). Modeling the pathways to self-confidence for graduate school in computing. *Research in Higher Education*, 62(3), 359-391. <https://doi.org/10.1007/s11162-020-09605-9>

Maher, M. A., **Wofford, A. M.,** Roksa, J., & Feldon, D. F. (2020). Finding a fit: Biological science doctoral students' selection of a principal investigator and research laboratory. *CBE—Life Sciences Education*, 19(3), Article 31. <https://doi.org/10.1187/cbe.19-05-0105>

Blaney, J. M., Kang, J., **Wofford, A. M.,** & Feldon, D. F. (2020). Mentoring relationships between doctoral students and postdocs in the lab sciences. *Studies in Graduate and Postdoctoral Education*, 11(3), 263-279. <https://doi.org/10.1108/SGPE-08-2019-0071>

Sax, L. J., **Wofford, A. M.,** George, K. L., Ramirez, D., & Nhien, C. (2020). *Advancing equity in graduate pathways: Examining the factors that sustain and develop computing graduate aspirations* [Paper presentation]. American Educational Research Association (AERA) Annual Meeting, San Francisco, CA. <http://tinyurl.com/vav8daf>

Lehman, K. J., **Wofford, A. M.,** Sendowski, M., Newhouse, K. N. S., & Sax, L. J. (2020). Better late than never: Exploring students' pathways to computing in later stages of college. In *Proceedings of the 51<sup>st</sup> ACM SIGCSE Technical Symposium on Computer Science Education (SIGCSE '20)*, 1075-1081. <https://doi.org/10.1145/3328778.3366814>

Maher, M. A., **Wofford, A. M.,** Roksa, J., & Feldon, D. F. (2020). Exploring early exits: Doctoral attrition in the biomedical sciences. *Journal of College Student Retention: Research, Theory, & Practice*, 22(2), 205-226. <https://doi.org/10.1177/1521025117736871>

Maher, M. A., **Wofford, A. M.,** Roksa, J., & Feldon, D. F. (2019). Doctoral student experiences in biological sciences laboratory rotations. *Studies in Graduate and Postdoctoral Education*, 10(1), 69-82. <https://doi.org/10.1108/SGPE-02-2019-050>

Gilmore, J. A., **Wofford, A. M.,** & Maher, M. A. (2016). The flip side of the attrition coin: Faculty perceptions of factors supporting graduate student success. *International Journal of Doctoral Studies*, 11, 419-439. Available at: <http://www.informingscience.org/Publications/3618>

## CHAPTER 1:

### INTRODUCTION AND BACKGROUND

*Each fall, just as the weather was turning from scorching summer heat to the cool, leafy breeze of the Midwest, I walked into the busiest days at the University of Missouri-Kansas City (UMKC) School of Medicine. For four years, my autumn days were characterized by reviewing thousands of graduate school applications from hopeful doctors and healthcare professionals. As the Admissions Coordinator for Graduate Programs, I facilitated the application, interview, and selection process for nine graduate-level programs. Throughout the application cycle, holistic admission was a primary emphasis in our review processes and training of committee members. In other words, there was not to be one aspect of an application that advanced potential candidates for admission; rather, admission would be determined from a summative evaluation of the applicant's overall potential contribution to UMKC and the larger profession.*

*As I reviewed applications from prospective students, I was frequently impressed with the extensive experiences and compelling narratives that applicants conveyed. Applicants often discussed their emerging exposure to medicine through their employment as a medical scribe or certified nursing assistant, were leaders in pre-professional healthcare organizations, and documented many hours volunteering in medicine—often via shadowing healthcare providers and traveling on medical mission trips. These non-cognitive experiences repeatedly set applicants apart from each other when their academic records were equally promising. In theory, adopting a holistic review process would help our programs be more equitable by facilitating the admission of students with an array of personal and professional backgrounds, rather than relying solely on traditional measures of “success” (e.g., test scores, GPA). Yet, as I screened applications each year, I felt two questions plaguing my curiosity: How were*

*prospective graduate students learning what features of their academic, extracurricular, and professional experiences to emphasize in their applications? And, which applicants had access to such a robust array of experiences in the first place?*

These questions set me on a path of curiosity about students' graduate school plans and preparation in scientific fields. Shortly after identifying these persistent questions, I found myself pursuing a Ph.D., learning more about the structures that uphold social and cultural inequities in various scientific fields (e.g., computing, biology, engineering), and trying to better understand the systemic and individual factors that shape trajectories to and through graduate school. As such, this three-article dissertation aims to advance what is known about the mechanisms that shape students' pathways to graduate degree programs in computing disciplines.

## **Introduction**

In recent years, students' post-college prospects have been highly influenced by staggering growth in the technology sector (Computing Research Association [CRA], 2017). Nearly 550,000 jobs in computing are expected to be created between 2018 and 2028 (Bureau of Labor Statistics [BLS], 2019), offering plentiful opportunities for bachelor's degree recipients to join the U.S. tech industry and reason to believe that the booming enrollments in undergraduate computing programs will continue to grow respectively (Barker et al., 2015). However, the promise of abundant job prospects in computing for bachelor's degree recipients also means that some key roles in computing—faculty positions in particular—are going unfilled, as they still require a graduate-level degree (BLS, 2019). As a result, collegiate computing departments face a severe faculty shortage (Flaherty, 2018).

Not only is there a dearth of faculty, but the computing professoriate also lacks diversity, most often discussed in relation to gender and race/ethnicity (Zweben & Bizot, 2018), leading to

a shortage of academic role models for students who have been historically minoritized in computing due to their social and cultural identities (e.g., gender, social class, race/ethnicity, dis/ability, sexuality). In order to advance equity in computing, there is a critical need to understand the factors that impact graduate school trajectories, especially among historically minoritized students in computing who could add necessary perspectives to the computing professoriate. Given the direct link between graduate school diversity and that among faculty (e.g., Cole & Barber, 2009; Hughes et al., 2017), the gatekeeping mechanisms in graduate school preparation and training stand to hinder key efforts to diversify the professoriate. Thus, without equitably fostering students' interest and development in computing graduate school pathways, computing departments may perpetuate inequities for decades to come.

### **The Unique Characteristics of Computing**

While scholars have highlighted many factors that affect students' graduate school plans within science, technology, engineering, mathematics, and medicine (STEMM) fields in the aggregate (e.g., Eagan et al., 2013; Szelényi & Inkelas, 2011; Xu, 2016), less attention has been given to the particular characteristics of computing graduate degree trajectories. Computing is uniquely situated in the STEMM landscape due to institutional-level complications from the undergraduate enrollment boom and challenges in creating more equitable learning environments and outcomes for historically minoritized students. In many ways, the unique characteristics of computing draw attention to the urgency of examining inequities in computing graduate school pathways. In terms of context, the tremendous growth that computing departments are experiencing is specific to computing fields (Barker et al., 2015; CRA, 2017), rather than STEMM as a whole. Although this surge in undergraduate enrollments is promising for the

future of computing professionals, it has also created many challenges. As stated in a recent CRA report (2017):

[The] discrepancy in students versus faculty has impacted the operation of programs. Many units face increased faculty retention problems, are not able to hire teaching faculty into newly created teaching positions, and realize that there are not enough new Ph.D.s to fill open faculty slots in the targeted areas (p. B-6).

Additionally, while several other STEMM disciplines (e.g., biology) have a surplus of doctoral recipients who wish to join the academic sector (Xue & Larson, 2015), the same cannot be said for computing disciplines. Students have many lucrative options to join the global tech industry after earning a bachelor's degree in computing (National Association of Colleges and Employers [NACE], 2018), which leads to fewer individuals pursuing a computing graduate degree and the faculty positions that may follow.

Further complicating the enrollment boom, computing departments face persistent challenges—both at the undergraduate and graduate level—to advancing equity and increasing the representation of historically minoritized students (e.g., Blaser et al., 2020; Stout & Wright, 2016; Zweben & Bizot, 2018). According to the 2017 CRA Taulbee Survey, women only make up approximately 20% of enrolled computer science students at the undergraduate and Ph.D. levels. Further, among undergraduate women enrolled in computer science majors, just 14% identify as Black or African American; Hispanic; Native Hawaiian or Pacific Islander; American Indian or Alaska Native—a percentage that drops to 4% at the doctoral level (Zweben & Bizot, 2018). While less is known about the representation and experiences of students facing structures

of minoritization beyond those concerning their gender and racial/ethnic identities, scholars are beginning to address additional, and perhaps intersecting, structural constraints to historically minoritized students' success in computing. For example, a recent study noted that women who identify as lesbian, gay, bisexual, transgender, or queer (LGBTQ) report the lowest sense of belonging in computing compared to LGBTQ men as well as heterosexual men and women at the undergraduate and graduate level (Stout & Wright, 2016). Overall, in comparison to other STEM disciplines, computing fields remain one of the least diverse (e.g., National Center for Science and Engineering Statistics [NCSES], 2019), which has critical implications for who advances the future of the tech industry and academic spaces in computing.

### **Shaping Computing Graduate School Pathways**

Individuals' decisions about graduate school are undoubtedly influenced by a plethora of factors, many of which have been studied among STEM students in the aggregate. Largely, prior research on STEM graduate pathways has highlighted the importance of structured research experiences (Eagan et al., 2013; Hunter et al., 2007; Pender et al., 2010), faculty and peer mentorship (Aikens et al., 2017; Cole & Espinoza, 2011; Faurot et al., 2013), and students' psychosocial traits—including self-efficacy, self-confidence, and disciplinary science identity—within such environments and interactions (Borrego et al., 2018; Byars-Winston et al., 2015; George & Wofford, 2019). Yet, it is imperative to better understand the experiences that shape students' *computing* graduate school pathways, given the unique context of computing and the ways that the disciplinary knowledge in computing diverges from other STEM fields.

Few studies have examined students' trajectories for graduate school in computing, and there are vital ways that the set of studies in this dissertation enhance the current conversation. Notably, while scholars have found faculty mentorship to guide students' aspirations and

decisions to earn a computing graduate degree (Cohoon et al., 2004; Cohoon & Lord, 2007; Wofford et al., forthcoming), I posit that the varying departmental roles of mentors in computing (e.g., faculty, staff, graduate students) and mentors' positional power in departments may shape students' mentoring experiences in distinct ways. Compounding the role of power in computing departments, historically minoritized students may also engage in mentoring interactions differently than their peers with systemically dominant identities. Further, while relationships in mentored learning environments (e.g., research programs) have been documented as salient factors of students' psychosocial development related to STEMM graduate pathways (e.g., Gazley et al., 2014; Merolla & Serpe, 2013; National Academies of Sciences, Engineering, and Medicine [NASEM], 2019), less is known about how specific mentoring practices affect students' psychosocial traits like self-efficacy and identity—traits that, in turn, are likely to shape students' pursuit of graduate-level computing (Wofford et al., forthcoming). As such, this dissertation focuses on how and for whom mentorship and psychosocial beliefs are fostered in undergraduate computing, particularly as these affective and relational experiences relate to expanding opportunity for students to pursue computing graduate school. It is also crucial to approach this work with an equity-minded perspective, which guides my approach for these studies and the recommendations I offer for computing departments.

### **Definition of Terms**

The present work seeks to interrogate and extend what is known about the influence of students' social identities, psychosocial beliefs, and mentoring experiences in computing on the development of key affective traits and plans to earn a graduate-level degree in a computing discipline. Given the prevalence of the concepts of equity and diversity in this dissertation, in

addition to the disciplinary focus on a specific set of subfields in STEMM, several key terms are central to each of the three studies that follow.

**Historically Minoritized Students:** Groups that vary from historically dominant and well-represented groups in computing by social and/or cultural identities. In line with Chase et al. (2014), I use the term “historically minoritized”—rather than “minority”—to reflect the social constructs of power in computing. When referring to minoritized racial/ethnic groups, specifically, I also use the term “underrepresented Students of Color in computing” (USOCC).

**Equity-Minded:** A lens analyzing how institutions create and sustain environments that perpetuate inequities among historically minoritized students (see Griffin, 2020; Peña et al., 2006). In this work, “equity” and “equitable” are used in a similar way to discuss structural changes that might create more socially just environments, experiences, and outcomes.

**Diversity:** The representation of groups with different demographic characteristics (e.g., social and cultural identities) and backgrounds. In a recent strategic plan, the National Science Foundation [NSF] (2011) defined diversity as “a collection of individual attributes that together help agencies pursue organizational objectives efficiently and effectively. These include, but are not limited to, characteristics such as national origin, language, race, color, disability, ethnicity, gender, age religion, sexual orientation, gender identity, socioeconomic status, veteran status, educational background, and family structures. The concept also encompasses differences among people concerning where they are from and where they have lived and their differences of thought and life experiences” (p. 3).

**STEMM:** Science, Technology, Engineering, Mathematics, and Medicine. Recent work by the NASEM (2019) has offered “STEMM” as an expanded definition of the more widely used acronym “STEM” in an effort to highlight medicine and healthcare-related fields as an important part of scientific disciplines. The NSF (2015) has included the following disciplines in “STEM”: agricultural, biological, and computer sciences; earth, atmospheric, and ocean sciences; mathematics and statistics; astronomy; chemistry; physics; aerospace, chemical, civil, electrical, industrial, materials, and mechanical engineering; social sciences, and psychology. In the scope of the present study, I do not include the social sciences and psychology alongside other STEMM disciplines.

**Computing:** Broadly includes computer science, computer engineering, software engineering, information systems, information technology, information science, security, and interdisciplinary fields such as data science and human computer interaction (Zweben & Bizot, 2015).

**Graduate School:** Master’s degree and Ph.D. In computing, these are the most common post-baccalaureate degrees (Zweben & Bizot, 2018). I do not include professional degrees or certificates when I discuss graduate education in computing. Additionally, I use the term “graduate aspirants” to refer to undergraduate students who have reported that they would like their highest degree earned to be a master’s or doctoral degree.

**Mentorship:** In accordance with a recent definition offered in *The Science of Effective Mentorship in STEMM* (NASEM, 2019), mentorship is defined as “a professional, working alliance in which individuals work together over time to support the personal and professional growth, development, and success of the relational partners through the provision of career and psychosocial support” (p. 2).

## Purpose and Scope of the Set of Studies

To contribute to research and practice that addresses disparities in computing graduate school pathways, this dissertation focuses on critically examining mentoring and psychosocial support among undergraduate students in computing. Structured across three articles, I explore (1) disparities in relation to what shapes computing graduate aspirants' self-confidence for getting admitted to graduate school in computing, (2) the (in)equitable nature of graduate aspirants' mentoring support in computing departments, as well as how departmental mentoring support is shaped by the mentor's role and students' social identities, and (3) how computing graduate students who mentor undergraduates make meaning of the ways in which their practices as mentors are reflective of and shaped by social identities as well as organizational structures and dynamics of the department and institution. Collectively, my dissertation highlights how computing departments might reimagine structures of equity-minded support for undergraduate students, and particularly support for undergraduates holding historically minoritized identities. Often, undergraduates' decisions about their post-baccalaureate trajectories involve their navigation of many discretionary structures and relationships. By focusing on mentoring and psychosocial development in computing departments, we can further understand how (in)equity in such mechanisms of support characterizes students' educational pathways in computing and—using the evidence in this dissertation—develop interventions to redress persistent opportunity gaps in the pursuit of computing graduate education.

Chapter 2 relied on quantitative approaches to examine how undergraduate students who took an introductory computing course develop self-confidence for admission to a computing graduate program. This study, *Modeling the Pathways to Self-Confidence for Graduate School in Computing*, was presented in fall 2019 as a peer-reviewed paper presentation at a national

conference and was published with *Research in Higher Education*. Focusing on disparities across students' gender and racial/ethnic identities, I used longitudinal survey data from the BRAID Research (Building, Recruiting, and Inclusion for Diversity) project to examine the predictive power of students' psychosocial beliefs and intro course support (from mentors and departments) on their self-confidence for computing graduate admission two years later after taking an intro course.

Chapter 3 was guided by the importance of psychosocial traits and the role of general mentoring support in analyses from Chapter 2. This study, *Inequitable Interactions? A Critical Quantitative Analysis of Mentorship and Psychosocial Development Within Computing Graduate School Pathways*, was presented in spring 2021 as a peer-reviewed paper presentation at a national conference. For this work, I used the same data source as the first study and drew from a sample of undergraduate students majoring in a computing field who held graduate school aspirations. Among students who identified having a primary mentor in their computing department, I examined how the nature of mentoring support (i.e., constructs based on specific mentoring behaviors), adapted from the College Student Mentoring Scale (CSMS; Crisp, 2009), may differentially predict graduate aspirants' development of computing self-efficacy and computing identity three or four years after taking an intro course.

Finally, Chapter 4 presents a study that qualitatively explored one type of mentoring—that between undergraduate computing students and their peers who are a “stage ahead” and currently in computing graduate school. This study, *Equity-Minded Stage-Ahead Mentoring: Exploring Graduate Students' Narratives as Mentors to Undergraduates in Computing*, focused on the perspectives of graduate student mentors. In doing so, findings from this study highlight how graduate student mentors considered their own identities and lived experiences (as well as

those of their mentee) in their mentoring approaches, and participants' narratives also document how organizational structures and dynamics of the computing department and institution offered unique affordances and constraints to graduate students engaging in stage-ahead mentorship.

The studies in this dissertation collectively enhance the literature base about computing graduate school pathways and mentoring relationships in computing, speaking to how computing departments can cultivate dynamic environments that promote equitable student outcomes and future plans in computing fields. If computing departments hope to promote equitable processes and increase diverse representation at the graduate level—and ultimately in the professoriate—it is necessary to understand how graduate aspirants experience departmental environments in computing as well as how current computing graduate students provide guidance to those who may be their future possible peers in graduate school.

### **Rationale for Three Studies**

Drawing on multiple methodologies and theoretical approaches, the three studies in this dissertation extend prior research in crucial ways. Relative to other post-college trajectories in computing, such as tech careers (e.g., Ross et al., 2020; Sax et al., 2019), little research has explored undergraduate students' plans for graduate school in computing (Blaney & Wofford, 2021; Cohoon et al., 2004; Cohoon & Lord, 2007; Wofford et al., forthcoming). In this dissertation, I contribute to this dearth of knowledge about students' computing graduate school trajectories using three distinct approaches. By first unveiling disparities among some of the factors that shape students' confidence for computing graduate school admission (Chapter 2), I identified further gaps and questions about students' mentoring experiences and psychosocial development (Chapters 3 and 4). Given the emphasis of mentorship and psychosocial attributes within prior publications concerning STEMM graduate school trajectories (e.g., Byars-Winston

et al., 2015; Eagan et al., 2013; NASEM, 2019), conducting a deeper examination of undergraduate students' mentoring interactions and domain-specific psychosocial beliefs in computing is vital to understanding the unique experiences that may underpin students' pursuit of a computing graduate degree.

The first study is a quantitative examination of undergraduate students' self-confidence in getting admitted to a graduate program in computing, focusing on gender and racial/ethnic inequities in such self-confidence. Using longitudinal data from the BRAID Research student surveys, this study primarily relied on a sample of undergraduate students who took a survey at the end of their introductory computing course in 2015-2016 and a follow-up survey in fall 2017, highlighting how students' self-confidence for computing graduate school admission changed during the two years that followed their intro course. I used structural equation modeling (SEM) to test an adapted version of social cognitive career theory (SCCT; Lent et al., 1994, 2000) in this study. Given the nature of SEM, the observed variables and constructs in this study reflected a narrow focus on the direct and indirect relationships between students' psychosocial beliefs and perceptions of support during and after their intro computing course. Throughout this study, I also grappled with the postpositivist paradigmatic traditions of some of the statistical methods employed with my personal commitment to critically advancing structural and systemic change in computing departments—a commitment that has only grown in the process of completing this dissertation. While intro courses have been emphasized as a way to garner more interest in computing among historically minoritized students (CRA, 2017), the ways in which students' graduate school pathways are shaped by intro course experiences and beliefs is not well understood. As such, this study makes a unique contribution to understanding inequities in disciplinary psychosocial development related to students' plans for computing graduate school.

Computing faculty and administrators may find the results of the first study especially useful. In light of the fact that not all intro course students are computing majors, these findings may inform departmental efforts to sustain non-majors' longer-term commitment to computing. In addition, results reveal salient changes—and inequities—in students' self-confidence for computing graduate admission in the two years following intro courses. Practically speaking, these changes are important for computing faculty and administrators to acknowledge, as such changes in self-confidence point indicate larger disparities in how USOCC, Asian and Asian American students, and women are supported relative to men and their white peers. Ultimately, computing self-efficacy emerged as the most important predictor of students' self-confidence for computing graduate admission, and I offer suggestions for policy and practice that can help computing departments equitably bolster students' confidence in being admitted to computing graduate school.

This first quantitative study, which controlled for several measures of students' disciplinary psychosocial beliefs and perceived support from mentors, in general, and departmental environments in computing, more specifically, laid the groundwork for the second and third studies. While mentoring support during students' introductory computing courses was part of the analyses in Chapter 2, the first study remained limited in its ability to address the longer-term role of mentorship, who students identified as mentors, or more particular aspects of the interactions or behaviors that students perceived being present in their mentoring relationships. As such, the studies in Chapters 3 and 4 attend to particular types of mentorship (i.e., more specific mentoring behaviors and roles of mentors themselves) and the psychosocial beliefs that mentoring relationships might foster for undergraduates as they consider computing graduate school. Further, analyses in the first study focused on gender and racial/ethnic

inequities and aggregated students' identities to better accommodate the parameter restrictions of structural equation modeling as a methodological approach; the second and third studies accounted for several additional social and cultural identities in an effort to better account for students' whole selves.

Chapter 3 includes a second quantitative study that employed a critical quantitative lens to focus on how graduate aspirants' experiences receiving departmental mentorship in computing (in)equitably shape their computing self-efficacy and computing identity three or four years after taking an intro computing course. This study was guided by Crisp et al.'s (2017) framework of mentoring undergraduate students and Ragins's (1995) theoretical framework of organizational change, which draws from literature on diversity, power, and mentorship to describe varying levels of power in organizations. Relying on longitudinal student survey data from the BRAID Research project, I used a sample of undergraduate computing students who took an introductory course survey in 2015-2016 or 2016-2017, a follow-up survey in fall 2019, held graduate aspirations at either time point, and identified having a mentor in their department (e.g., faculty advisor, graduate student, academic advising staff) on the follow-up survey. Among graduate aspirants with departmental mentors in computing, I first employed descriptive tests to explore the nature of mentorship, focusing on inequities across the role (and positional power) of departmental mentors and across students' social identities. Then, I tested two OLS regression models to examine the extent to which different aspects of mentoring relationships shape computing self-efficacy and identity, centering on particular types of mentoring support (i.e., psychological and emotional support, degree completion support, computing field and career development support), adapted from Crisp (2009). Additionally, I used interaction terms to

understand how forms of mentoring support might differentially affect graduate aspirants' psychosocial development.

Several recent publications from national organizations (Crisp et al., 2017; NASEM, 2019) have drawn increased attention to social justice issues related to the mentorship of undergraduate students, especially those in STEMM. By focusing specifically on mentorship in computing departments, findings from this second quantitative study may be of particular interest to departmental leaders interested in critically understanding how mentoring experiences can be interpreted with attention to structural and cultural levels of power in computing departments. By focusing on disparities across graduate aspirants' experiences with departmental mentorship in computing, as well as how aspects of such mentoring relationships inequitably shape disciplinary self-efficacy and identity, computing faculty and staff may gain awareness of how mentoring experiences can be (re)shaped to create more equitable support structures. In turn, enhancing equitable forms of mentoring support may result in more historically minoritized graduate aspirants translating their stated goals for a graduate degree into concrete application and matriculation behaviors. As discussed above, mentorship and psychosocial development have both been emphasized as key aspects of undergraduate training that enhance STEMM graduate school pathways; however, little is known about the relationship between these relationships and beliefs in computing. By better understanding the inequitable effects of departmental mentorship on psychosocial development, computing departments can use these results to transform the structure and culture of mentorship with an equity-minded perspective.

Despite these two quantitative studies making significant inroads to understanding students' graduate school trajectories in computing, some features of mentoring relationships remain obscured by quantitative analyses. Specifically, the preceding studies are limited in their

ability to discuss mentoring relationships with particular individuals or how mentors see their own role and identities impacting their approach to mentoring undergraduates. In other words, the ways in which mentors' interactions shape students' psychosocial development and post-college plans may be particular to the departmental role, social identities, and lived experiences of the mentors themselves. Given these limitations and the need to discuss mentorship with attention to the perspectives of those in a mentoring position of power (i.e., mentors), the third study in this dissertation used a qualitative approach to understand the perspectives of graduate students in computing who serve as mentors to undergraduate computing students (i.e., "stage-ahead mentors").

The study described in Chapter 4 employed narrative inquiry to understand the experiences of stage-ahead mentors in computing. Amid the current enrollment boom, graduate students are often being tasked with the "faculty work" of teaching and advising/mentoring (CRA, 2017), yet very little research even raises the concept of computing graduate students being mentors (Boyer et al., 2010; Tashakkori et al., 2005). Stage-ahead mentors might have unique ways of engaging in mentorship compared to others in the department, such as faculty, and discerning how stage-ahead mentors make meaning of their mentoring approaches with undergraduate students in computing can enhance what is known about the ways mentorship is learned and practiced by those who may soon be faculty members themselves. Guided by Griffin's (2020) equity-minded mentoring model (EM<sup>3</sup>) and a critical constructivist paradigm (Kincheloe, 2005), I explored graduate-undergraduate mentorship in computing through the narratives of doctoral students in informatics—a growing sub-field in computing. Specifically, I used education journey mapping (Annamma, 2017) and facilitated in-depth interviews to (re)construct mentors' narratives. The examination of graduate students' perspectives in this

third study is strategic, as I aimed to address the ways that graduate students build relationships with undergraduates and perhaps indirectly foster undergraduate students' interest for computing graduate school. Additionally, understanding the ways that stage-ahead mentors view their mentoring approaches to be reflective of and shaped by social identities (of mentors and mentees) as well as larger departmental and institutional structures has critical implications for knowing the extent to which mentoring relationships in computing embody the dimensions of equity-minded mentorship. Cumulatively, these findings can inform institutional actions toward incentivizing and rewarding graduate students for engaging in stage-ahead mentorship, and there is also a need to clarify expectations of stage-ahead mentorship with identity and power dynamics in mind. Given that stage-ahead mentors will likely go on to hold leadership roles in academia as well as the computing industry, it is crucial that the process of learning how to mentor in equity-minded ways is structurally supported as a key piece of doctoral training.

### **Restricting the Scope**

In light of taking both a broad focus on computing disciplines and a specific focus on informatics in the present work, it is important to acknowledge that findings may not be applicable to all subfields of computing. It is also the case that, across all three studies, these findings speak to environments of computing departments at doctoral-granting institutions with high research activity, given the nature of the analytic samples. Thus, findings may be primarily transferrable to similar types of universities, leaving much to be explored about computing environments, students' development, and structures of mentorship at other types of institutions. In addition, these study samples are intentionally restricted in ways to focus on particular features of students' trajectories to and through computing graduate degree programs; however, each restriction offers plentiful opportunities for future research.

## **Researcher Positionality**

While I have long been committed to the translation of research to practice in education, my motivations for interrogating structures of power and systemic oppression in postsecondary STEM settings have grown significantly in recent years. My undergraduate training as a high school teacher cultivated my original dedication to supporting students' educational trajectories. However, I have since realized how the individual-level focus of my undergraduate training (as opposed to a systems-level perspective) and the geography in which I learned to be a teacher (rural Missouri) largely protected the permeance of whiteness in education that I benefit from as a white woman. My master's program held a deeper commitment to social justice, which catalyzed me to critically examine how minoritization is socially constructed. Working full-time in graduate admissions for a medical school while engaging with this curriculum as a part-time master's student prompted me to contend with how I saw systems like classism, ableism, racism, and transphobia materialize in admissions processes—and how I stood as a benefactor in these systems while combatting gendered patriarchal norms. My dedication for equitable educational opportunities has only grown in my doctoral program, and I continue to (un)learn and (re)commit myself to transformative education in new ways each day.

Much of the research I have pursued as a Ph.D. student has been shaped by these earlier postsecondary and professional experiences, especially when it comes to reimagining collegiate practices and policies that may disrupt persistent inequities in STEM trajectories. I also carry motivations from earlier personal experiences, as my parents' service-oriented vocations taught me to prioritize community care and empathy—values that I have often experienced in acts of affirming mentorship. My personal engagement with mentorship inspired me to explore how mentoring could serve as a mechanism of change to advance more equitable processes in higher

education, and this became a key focus of the studies in this dissertation. While generating the corpus of data for the qualitative study about stage-ahead mentorship (Chapter 4), I created my own education journey map (Annamma, 2017) about mentorship I have provided and received throughout my trajectory. Engaging in mapmaking with an eye toward reflexivity and reciprocity helped me better understand how the successes and tensions I have faced in my mentoring experiences are embedded within larger power dynamics and social systems; I share this map in Figure 1 to foreground how I come to this research.

### **Significance of the Work**

Enhancing equitable structures, interactions, and processes in graduate school pathways has crucial implications for shaping the trajectories and experiences of future faculty in any discipline. In computing, the need for equity-minded practices—as a way to challenge toxic environments and facilitate diversity—in graduate school pathways is urgent, especially given the faculty shortage and lack of diversity within the professoriate. By using three distinct studies with divergent theoretical, empirical, and epistemological perspectives, this dissertation makes a significant contribution to understanding how mentoring interactions and psychosocial beliefs shape students' graduate school trajectories in computing disciplines. In addition, findings from these studies can be used to support equity-minded changes to institutional as well as national policy and practice. Although students' decisions to attend graduate school are often thought of in an individual lens of personal agency, the implications offered with each article serve to complicate this notion and point to several ways in which post-baccalaureate educational trajectories—and the mentoring interactions within such—are products of complex social systems and organizational dynamics. It is my hope that these implications serve as a starting

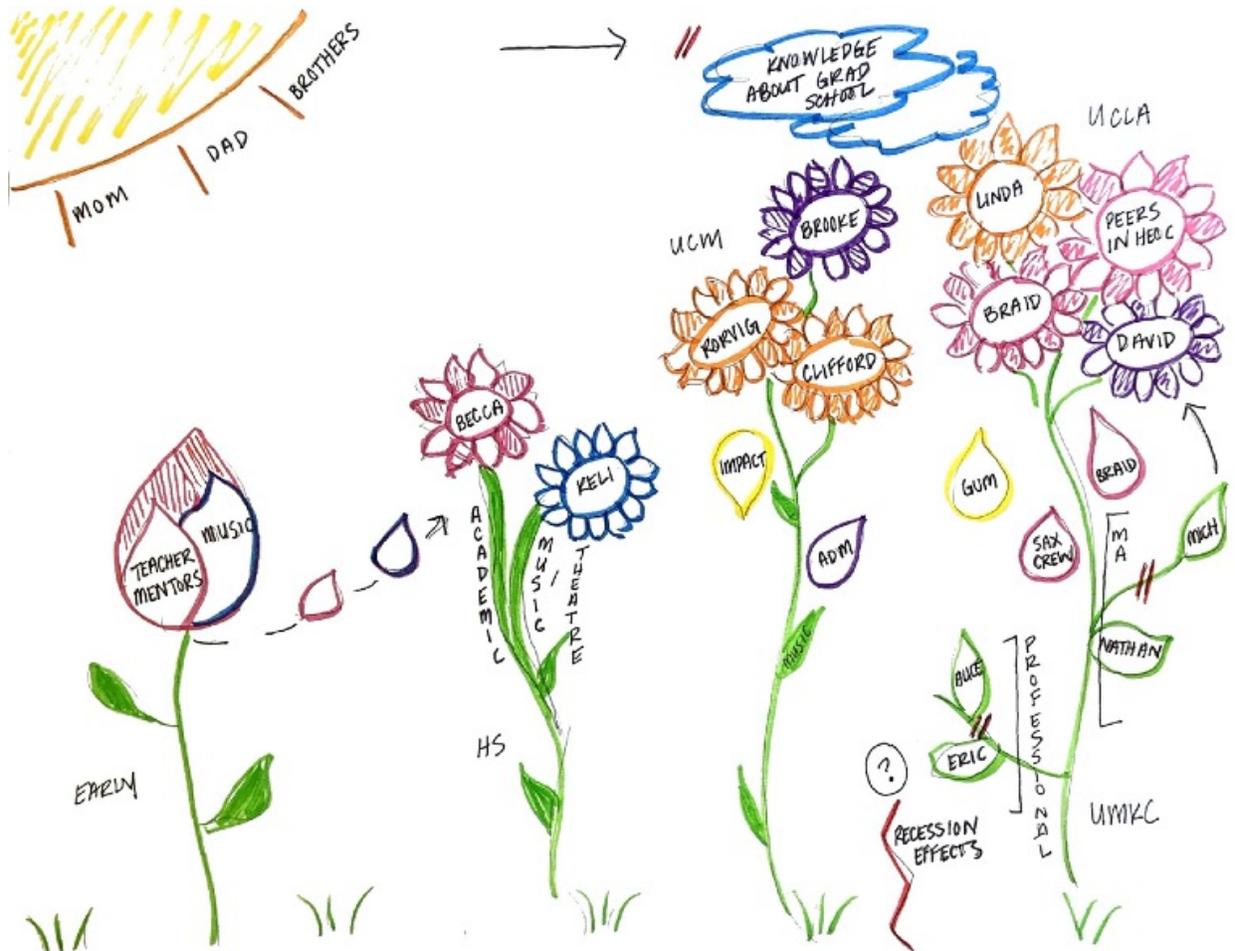
point to help leaders at both institutions and national organizations consider new, equity-minded initiatives in policy and practice.

### **Conclusion**

When I first began contemplating why certain applicants for medical graduate programs had specific experiences and resources, I was unaware that those questions would guide my passion and motivation for so many years to follow. Not only has that been the case but engaging with this work has already raised new questions, ideas, and opportunities to bring a critical eye to mentorship and graduate school trajectories in STEMM. With this dissertation, I hope computing faculty, staff, and students will use the present evidence to produce equity-minded interventions for graduate school pathways in computing. Ultimately, changing the larger cultures of mentorship and structures of psychosocial development may offer vital ways for computing departmental leaders to rewrite the script, thus advancing equitable access, relationships, and post-baccalaureate transitions toward graduate school in computing.

Figure 1

Mentoring Journey Map of Annie Wofford



## References

- Aikens, M. L., Robertson, M. M., Sadselia, S., Watkins, K., Evans, M., Runyon, C. R., Eby, L. T., & Dolan, E. L. (2017). Race and gender differences in undergraduate research mentoring structures and research outcomes. *CBE—Life Sciences Education*, 16(2), Article 34. <https://doi.org/10.1187/cbe.16-07-0211>
- Annamma, S. A. (2017). Disrupting cartographies of inequity: Education journey mapping as a qualitative methodology. In D. Morrison, S. A. Annamma, & D. D. Jackson (Eds.), *Critical race spatial analysis: Mapping to understand and address educational inequity* (pp. 35–50). Stylus Publishing, LLC.
- Barker, L., Camp, T., Walker, E., & Zweben, S. (2015). Expanding the pipeline: Booming enrollments—what is the impact? *Computing Research News*, 27(5), 52-53.
- Blaney, J. M., & Wofford, A. M. (2021). Fostering Ph.D. aspirations among upward transfer students in computing. *Computer Science Education*. Advance online publication. <https://doi.org/10.1080/08993408.2021.1929723>
- Blaser, B., Bennett, C., Ladner, R. E., Burgstahler, S. E., & Mankoff, J. (2020). Perspectives of women with disabilities in computing. In C. Frieze & J. L. Quesenberry (Eds.), *Cracking the digital ceiling: Women in computing around the world* (pp. 159-182). Cambridge University Press.
- Borrego, M., Knight, D. B., Gibbs, K., & Crede, E. (2018). Pursuing graduate study: Factors underlying undergraduate engineering students' decisions. *Journal of Engineering Education*, 107(1), 140–163. <https://doi.org/10.1002/jee.20185>
- Boyer, K. E., Thomas, E. N., Rorrer, A. S., Cooper, D., & Vouk, M. A. (2010). Increasing technical excellence, leadership and commitment of computing students through identity-based mentoring. *Proceedings of the 41st ACM Technical Symposium on Computer Science Education (SIGCSE '10)*, 167–171. <https://doi.org/10.1145/1734263.1734320>
- Bureau of Labor Statistics. (2019). *Occupational outlook handbook: Computer and information technology occupations*. U.S. Department of Labor. <https://www.bls.gov/ooh/computer-and-information-technology/home.htm>
- Byars-Winston, A. M., Branchaw, J., Pfund, C., Leverett, P., & Newton, J. (2015). Culturally diverse undergraduate researchers' academic outcomes and perceptions of their research mentoring relationships. *International Journal of Science Education*, 37(15), 2533–2554. <https://doi.org/10.1080/09500693.2015.1085133>
- Chase, M. M., Dowd, A. C., Pazich, L. B., & Bensimon, E. M. (2014). Transfer equity for “minoritized” students: A critical policy analysis of seven states. *Educational Policy*, 28(5), 669-717. <https://doi.org/10.1177/0895904812468227>

- Cohoon, J. M., Gonsoulin, M., & Layman, J. (2004). Mentoring computer science undergraduates. In K. Morgan, J. Sanchez, C. A. Brebbia, & A. Voiskounsky (Eds.), *Human perspectives in the internet society: Culture, psychology and gender* (pp. 199–208). WIT Press.
- Cohoon, J. M., & Lord, H. (2007). Women's entry to graduate study in computer science and computer engineering in the United States. In C. J. Burger, E. G. Creamer, & P. S. Meszaros (Eds.), *Reconfiguring the firewall: Recruiting women to information technology across cultures and continents* (pp. 147–160). AK Peters, Ltd.
- Cole, D., & Espinoza, A. (2011). The postbaccalaureate goals of college women in STEM. *New Directions for Institutional Research*, 2011(152), 51–58. <https://doi.org/10.1002/ir.408>
- Cole, S., & Barber, E. (2009). *Increasing faculty diversity: The occupational choices of high-achieving minority students*. Harvard University Press.
- Computing Research Association (2017). *Generation CS: Computer science undergraduate enrollments surge since 2006*. <https://cra.org/data/Generation-CS/>
- Crisp, G. (2009). Conceptualization and initial validation of the College Student Mentoring Scale (CSMS). *Journal of College Student Development*, 50(2), 177-194. <https://doi.org/10.1353/csd.0.0061>
- Crisp, G., Baker, V. L., Griffin, K. A., Lunsford, L. G., & Pifer, M. J. (2017). Mentoring undergraduate students. *ASHE Higher Education Report*, 43(1), 7–103. <https://doi.org/10.1002/aehe.20117>
- Eagan, M. K., Hurtado, S., Chang, M. J., Garcia, G. A., Herrera, F. A., & Garibay, J. C. (2013). Making a difference in science education: The impact of undergraduate research programs. *American Educational Research Journal*, 50(4), 683–713. <https://doi.org/10.3102/0002831213482038>
- Faurot, M. E., Doe, F., Jacobs, E. R., Lederman, N. G., & Brey, E. M. (2013). From the undergraduate student perspective: The role of graduate students in an undergraduate research program. *120th ASEE Annual Conference & Exposition*, 1–12.
- Flaherty, C. (2018, May 9). *System crash*. Inside Higher Ed. <https://www.insidehighered.com/news/2018/05/09/no-clear-solution-nationwide-shortage-computer-science-professors>
- Gazley, J. L., Remich, R., Naffziger-Hirsch, M. E., Keller, J., Campbell, P. B., & McGee, R. (2014). Beyond preparation: Identity, cultural capital, and readiness for graduate school in the biomedical sciences. *Journal of Research in Science Teaching*, 51(8), 1021–1048. <https://doi.org/10.1002/tea.21164>
- George, K. L., & Wofford, A. M. (2019, April 5-9). *Relationships with faculty and self: Examining the factors that contribute to STEM graduate degree intentions* [Paper

- presentation]. American Educational Research Association Annual Meeting, Toronto, ON, Canada.
- Griffin, K. A. (2020). Rethinking mentoring: Integrating equity-minded practice in promoting access to and outcomes of developmental relationships. In A. Kezar and J. Posselt (Eds.), *Higher education administration for social justice and equity: Critical perspectives for leadership* (pp. 93-110). Routledge.
- Hughes, C. C., Schilt, K., Gorman, B. K., & Bratter, J. L. (2017). Framing the faculty gender gap: A view from STEM doctoral students. *Gender, Work & Organization*, 24(4), 398–416. <https://doi.org/10.1111/gwao.12174>
- Hunter, A.-B., Laursen, S. L., & Seymour, E. (2007). Becoming a scientist: The role of undergraduate research in students' cognitive, personal, and professional development. *Science Education*, 91(1), 36–74. <https://doi.org/10.1002/sce.20173>
- Kincheloe, J. L. (2005). *Critical constructivism primer* (Vol. 2). Peter Lang.
- Lent, R. W., Brown, S. D., & Hackett, G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice, and performance. *Journal of Vocational Behavior*, 45(1), 79-122.
- Lent, R. W., Brown, S. D., & Hackett, G. (2000). Contextual supports and barriers to career choice: A social cognitive analysis. *Journal of Counseling Psychology*, 47(1), 36-49. <https://doi.org/10.1037/0022-0167.47.1.36>
- Merolla, D. M., & Serpe, R. T. (2013). STEM enrichment programs and graduate school matriculation: The role of science identity salience. *Social Psychology of Education*, 16(4), 575-597. <https://doi.org/10.1007/s11218-013-9233-7>
- National Center for Science and Engineering Statistics (2019). *Women, minorities, and persons with disabilities in science and engineering: 2019* (NSF Special Report 19-304). National Science Foundation. <https://www.nsf.gov/statistics/wmpd>
- National Academies of Sciences, Engineering, and Medicine. (2019). *The science of effective mentorship in STEMM*. The National Academies Press. <https://doi.org/10.17226/25568>
- National Association of Colleges and Employers. (2018). *First destinations for the college class of 2017: Findings and analysis*. NACE Center for Career Development and Talent Acquisition. <https://www.naceweb.org/job-market/graduate-outcomes/first-destination/class-of-2017/>
- National Science Foundation. (2011). *National Science Foundation's Diversity and Inclusion Strategic Plan 2012-2016*. <https://www.nsf.gov/od/odi/reports/StrategicPlan.pdf>

- National Science Foundation, National Center for Science and Engineering Statistics. (2015, June 30). *Science and engineering degrees: 1966-2012* (Appendix B, NSF 15-326). <https://www.nsf.gov/statistics/2015/nsf15326/>
- Peña, E. V., Bensimon, E. M., & Colyar, J. (2006). Contextual problem defining: Learning to think and act from the standpoint of equity. *Liberal Education*, 92(2), 48-55.
- Pender, M., Marcotte, D. E., Sto. Domingo, M. R., & Maton, K. I. (2010). The STEM pipeline: The role of summer research experience in minority students' Ph.D. aspirations. *Education Policy Analysis Archives*, 18(30), 1–36.
- Ragins, B. R. (1995). Diversity, power, and mentorship in organizations: A cultural, structural, and behavioral perspective. In M. M. Chemers, S. Oskamp, & M. Constanzo (Eds.), *Diversity in organizations: New perspectives for a changing workplace* (pp. 91–132). SAGE Publications.
- Ross, M., Hazari, Z., Sonnert, G., & Sadler, P. (2020). The intersection of being Black and being a woman: Examining the effect of social computing relationships on computer science career choice. *ACM Transactions on Computing Education (TOCE)*, 20(2), 1–15. <https://doi.org/10.1145/3377426>
- Sax, L. J., George, K. L., Wofford, A.M., Sundar, S. (2019, November 14-16). *The tech trajectory: Examining the role of college environments in enhancing a diverse pipeline to computing careers* [Paper presentation]. Association for the Study of Higher Education Annual Meeting, Portland, OR, United States.
- Stout, J. G., & Wright, H. M. (2016). Lesbian, gay, bisexual, transgender, and queer students' sense of belonging in computing: An intersectional approach. *Computing in Science & Engineering*, 18(3), 24-30. <https://doi.org/10.1109/MCSE.2016.45>
- Szelényi, K., & Inkelas, K. (2011). The role of living-learning programs in women's plans to attend graduate school in STEM fields. *Research in Higher Education*, 52(4), 349-369. <https://doi.org/10.1007/s11162-010-9197-9>
- Tashakkori, R., Wilkes, J. T., & Pekarek, E. G. (2005). A systemic mentoring model in computer science. *Proceedings of the 43rd Annual Southeast Conference (ACM-SE 43)*, 1, 371-375. <https://doi.org/10.1145/1167350.1167453>
- Wofford, A. M., Sax, L. J., George, K. L., Ramirez, D., & Nhien, C. (forthcoming). Advancing equity in graduate pathways: Examining the factors that sustain and develop computing graduate aspirations. *The Journal of Higher Education*.
- Xu, Y. J. (2016). Aspirations and application for graduate education: Gender differences in low participation STEM disciplines. *Research in Higher Education*, 57(8), 913-942. <https://doi.org/10.1007/s11162-016-9411-5>

Xue, Y., & Larson, R. C. (2015). STEM crisis or STEM surplus? Yes and yes. *Monthly Labor Review*. <https://doi.org/10.21916/mlr.2015.14>

Zweben, S. H., & Bizot, E. B. (2015). Representation of women in postsecondary computing 1990–2013: Disciplines, institutional, and individual characteristics matter. In *Proceedings of the 2015 Research in Equity and Sustained Participation in Engineering, Computing, and Technology (RESPECT)*, 1–8. <https://doi.org/10.1109/RESPECT.2015.7296493>

Zweben, S., & Bizot, B. (2018). *2017 CRA Taulbee survey: Another year of record undergrad enrollment; doctoral degree production steady while master's production rises again*. Computing Research Association. <https://cra.org/wp-content/uploads/2018/05/2017-Taulbee-Survey-Report.pdf>

**CHAPTER 2:**  
**MODELING THE PATHWAYS TO SELF-CONFIDENCE FOR GRADUATE SCHOOL**  
**IN COMPUTING**

**Introduction**

Undergraduate computing programs<sup>1</sup> are experiencing significant growth when it comes to enrollment but face a critical shortage of faculty to teach and advise undergraduate students (Flaherty, 2018; National Academies of Sciences, Engineering, and Medicine [NASEM], 2017; Singer, 2019). Computing faculty play a key role in such instruction and in training a diverse workforce to represent national needs (Payton & Souvenir, 2016). However, there is a vital disconnect in the faculty pipeline: getting undergraduate students to and through graduate school (i.e., master’s and doctoral programs). While a Ph.D. is often required to work as computing faculty (Mandel & Mache, 2017), a master’s degree may be an intermediate step to a Ph.D. Thus, there is a need to examine graduate school plans as inclusive of master’s and doctoral degrees.

In addition, those who do earn Ph.D.s in computing often do not reflect the demographic identities of the students they may serve. Specifically, over half of computing Ph.D.s are international students—many of whom return to their countries of origin after graduating (Hambrusch et al., 2015). And, in 2017, women earned only 19.3% of computing Ph.D. degrees, Asian American students were awarded 9.3%, and underrepresented Students of Color in computing (USOCC)<sup>2</sup> cumulatively earned just 3.2% of computing doctorates (Zweben & Bizot, 2018). Further complicating the problem, it appears that either market incentives (e.g., high

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<sup>1</sup> “Computing” can be understood broadly as a group of subfields that include computer science, computer engineering, information science, and varying interdisciplinary subfields (e.g., data science).

<sup>2</sup> I define USOCC to include students identifying as Black or African American; Hispanic or Latina/o/x; American Indian or Alaska Native; or Arab, Middle Eastern, or Persian, drawing from Tamer & Stout’s (2016b) definition.

earning potential) continue to draw computing doctoral recipients to industry positions instead of academia (NASEM, 2017; Singer, 2019), or that graduate school dissuades students from pursuing the professoriate (Rorrer et al., 2018). At a time when schools are seeking to increase diversity in undergraduate computing majors and courses (Beyer, 2014), institutions should also focus on fostering diverse computing *graduate* programs. Without increasing equity in computing graduate school and faculty pipelines, undergraduate students who have historically been left at the margins in computing (e.g., women, USOCC) may lack role models (Tamer & Stout, 2016a), face adverse classroom settings, and perhaps leave computing altogether (NASEM, 2017).

In order for computing departments to diversify the graduate pipeline, they need to build students' academic confidence early, beginning with introductory (intro) courses. Academic self-confidence, often formed in students' undergraduate years, is key in shaping graduate school plans (Eagan et al., 2013), but confidence may be moderated by gender, race/ethnicity, or other identities. As such, it is vital to examine students' self-confidence in being admitted to graduate school and how this confidence relates to students' identities, perceptions, and experiences. By exploring what affects undergraduates' confidence in computing graduate school admission, departments will be better able to invest in experiences that increase self-confidence among computing graduate school aspirants. Further, identifying the salience of certain experiences in building confidence among women and Students of Color (i.e., USOCC, Asian/Asian American students) may help strengthen and diversify the future graduate school applicant pool. The purpose of this study is to investigate the predictors of students' self-confidence related to computing graduate school admission. The following questions frame this inquiry:

1. What are the social/cultural identities and academic characteristics of students who indicated high self-confidence in being admitted to a computing graduate degree program?
2. How does low, average, and high self-confidence in being admitted to a computing graduate program change over time, and how does this vary by race/ethnicity and gender?
3. What experiences and interactions directly and indirectly predict students' self-confidence in being admitted to a graduate program in computing, and how do mediating relationships vary by race/ethnicity and gender?

By addressing these questions, this study uncovers critical details about students' self-confidence for graduate-level computing programs. Such information has key implications for advancing equity throughout the pathways to computing graduate school.

### **Literature Review and Conceptual Framework**

This study focuses on how students' psychosocial beliefs and perceptions of external support shape their self-confidence in computing graduate school admission, as well as the gender and racial/ethnic inequities within these experiences. As such, social cognitive career theory (SCCT; Lent et al., 1994, 2000) was a useful framework to test how students' perceptions in undergraduate computing map on to later academic beliefs. Using SCCT as a theoretical base, this study examined how self-confidence for computing graduate admission may be predicted by students' beliefs within and following intro computing courses. Hence, I posited several direct and indirect relationships among students' experiences and psychosocial traits. First, I outline the origins and applicability of SCCT for this study. Then, I provide justification for assessing self-confidence as the outcome. Third, using SCCT's framing (i.e., personal inputs and contextual influences, learning experiences and self-efficacy, and outcome expectations), I discuss this

study’s application of each component and how prior literature investigating graduate aspirations and affective development in computing, as well as science, technology, engineering, mathematics, and medicine (STEMM<sup>3</sup>) more broadly, supports these selections.

### **Social Cognitive Career Theory**

Drawing from Bandura’s (1977, 1997) social cognitive theory, SCCT includes three dynamic models capturing iterative experiential and cognitive processes shaping academic and career paths: the interest, choice, and performance models (Lent et al., 1994). Figure 1 shows that SCCT’s primary tenets include self-efficacy (i.e., “Can I do this?”), outcome expectations (i.e., “What will happen if I do this?”), and resultant interests, goals, and performance outcomes (Lent et al., 1994). This study, like others (e.g., Herrera et al., 2011), focused on one piece of SCCT—the interest model. The interest model is the first of three SCCT models (followed by models examining career/academic choice and performance), and the interest model facilitates our initial understanding of how students develop beliefs about computing graduate school.

SCCT draws from Bandura’s (1986) concept of *triadic reciprocity*, positing that one’s personal attributes and context work in tandem with perceptions of external environments and behaviors to shape individuals’ educational and vocational decisions. In order to more accurately assess specific contextual perceptions, this study included several computing-specific measures. By analyzing SCCT’s premise of educational interests in computing, this study extends research testing SCCT using structural equation modeling (SEM; e.g., Byars-Winston & Fouad, 2008) and work using SCCT to study STEMM educational aspirations (e.g., Cole & Espinoza, 2011). The present study uniquely investigates students’ disciplinary-specific beliefs spanning the two

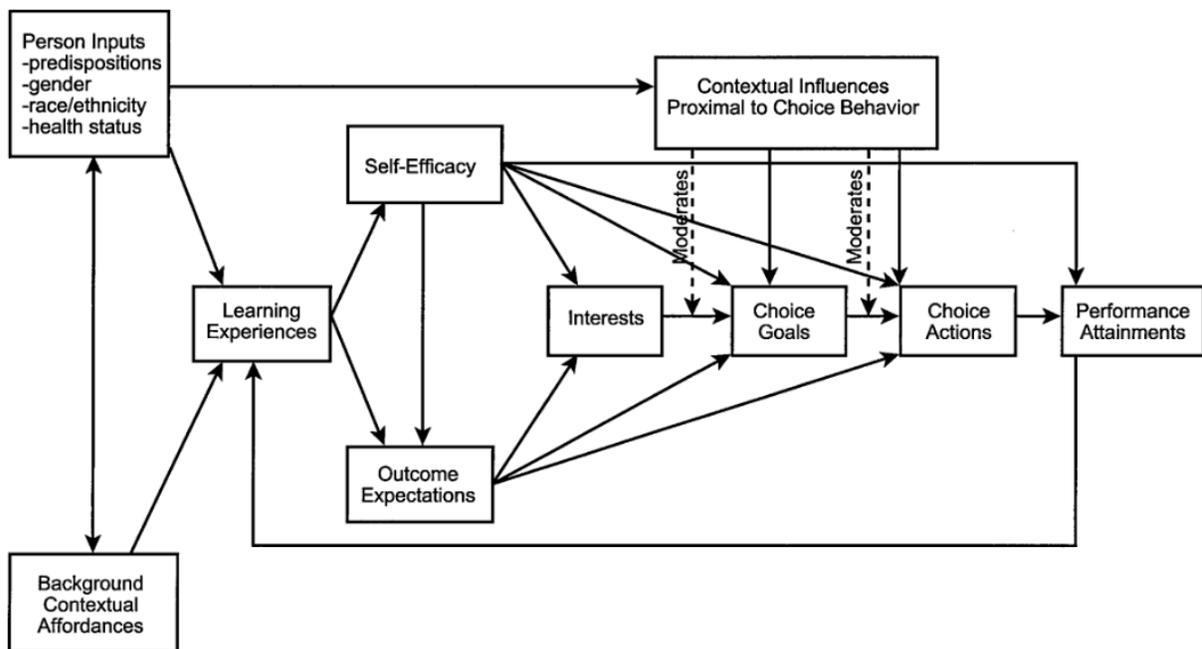
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<sup>3</sup> Aligning with a recent report by the NASEM (2019), I use “STEMM” throughout this work to explicitly account for medicinal-related fields as the second “M,” as opposed to the more common acronym of “STEM.”

years following intro courses, guided by SCCT and methodology that tests theoretical notions about (in)equities in psychosocial development, thus making a vital contribution to research on diversifying educational trajectories in computing. As undergraduate enrollment grows and departments emphasize the role of intro courses in diversifying computing, it is of utmost importance that we know how students’ beliefs in these courses—alongside other experiences and self-assessments—affect later educational paths.

**Figure 1**

*Social Cognitive Career Theory*



*Note.* Reprinted from *Journal of Vocational Behavior*, 45, R. W. Lent, S. D. Brown, and G. Hackett, “Toward a Unifying Social Cognitive Theory of Career and Academic Interest, Choice, and Performance,” 79–122, Copyright (1994), with permission from Elsevier.

## **Self-Confidence, Interests, and Intentions for STEMM Graduate School**

In SCCT, individuals' interests precede their career-relevant choices and actions (Lent et al., 2000). Lent et al. also noted that positive environmental factors, like support networks, facilitate the process of turning interests into actions. By focusing on self-confidence for computing graduate school admission, this study highlights a key aspect that may link graduate school interests to actions toward application: students' perceived self-confidence. I define self-confidence as students' general self-assessment of their academic and intellectual abilities, which may be heavily affected by social relationships and longer-term values (Sander & Sanders, 2006). Notably, self-efficacy differs from self-confidence in that self-efficacy focuses on one's motivation and self-assessment of specific skills (Bandura, 1977). I separate these constructs to illustrate how self-efficacy may predict self-confidence but may also relate to other psychosocial beliefs.

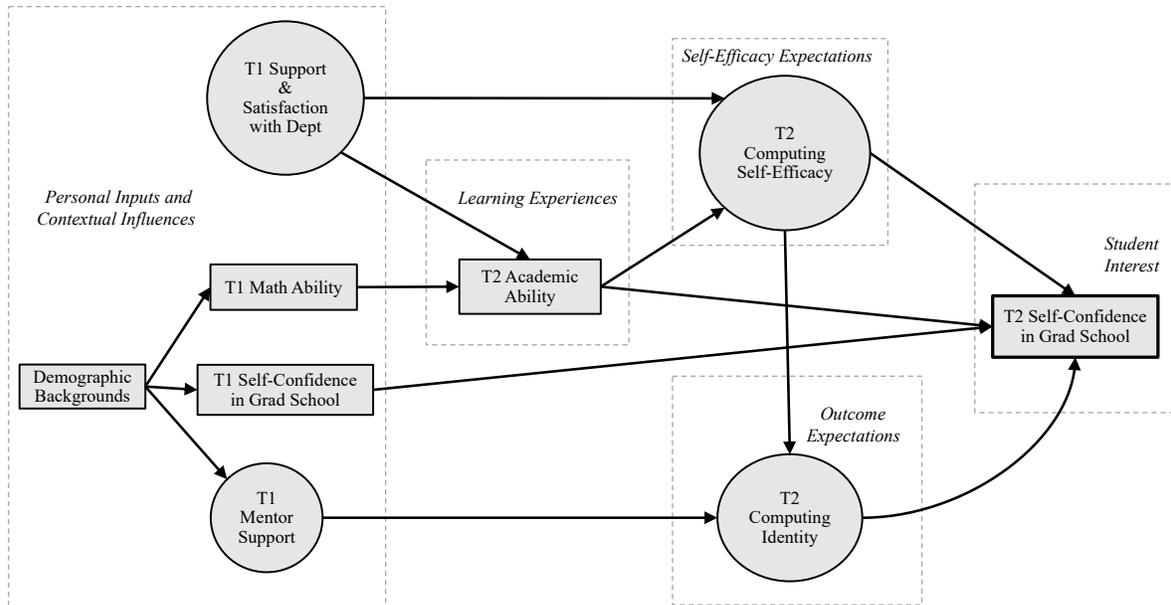
In the aggregate, literature has suggested that STEMM graduate school paths are affected by undergraduate research experiences (UREs) and peer communities (Eagan et al., 2013; Kyoung Ro et al., 2017), faculty mentorship (Cole & Espinoza, 2011; Eagan et al., 2013; Sax, 2001), debt and future earnings (Malcom & Dowd, 2012; Xu, 2016), and the internalization of abilities via self-efficacy or identity (Kyoung Ro et al., 2017; Merolla & Serpe, 2013; Szelényi & Inkelas, 2011). Scholars have also stressed the importance of mediating effects in STEMM graduate pathways (Merolla & Serpe, 2013; Strayhorn, 2010), and these complex relationships—as well as the inequalities within them—warrant further research. Importantly, research has also started advancing a critical lens of Asian/Asian American students' experiences in STEMM, as numerical representation may not erase stereotyping and discrimination (Trytten et al., 2012). In analyzing students' self-confidence for computing graduate school admission, with particular

attention to how pathways differ for women, Asian/Asian American students, and USOCC, this study helps demystify some of these known effects for one unique STEMM field.

Recently, scholars have made the case for disciplinary disaggregation by noting how varied STEMM fields are and how equity differentially operates within each context (Rocconi et al., 2015; Sax & Newhouse, 2019). For example, Rorrer et al. (2018) found that computing UREs may actually decrease students' interest in graduate school—contradicting larger support for UREs in STEMM (Eagan et al., 2013; Kyoung Ro et al., 2017). Further, collaborative spaces—like those of research—have been endorsed as environments from which to recruit women for computing graduate programs (Cuny & Aspray, 2002). Though prior work has operationalized collaboration via UREs, computing departments are also an important space for early community building. This study extends our knowledge of collaborative spaces in computing by studying students' perceived departmental support during their intro courses. In addition, and akin to SCCT's focus on self-efficacy, Figure 2 shows the hypothesis that self-confidence in computing graduate admission was indirectly related to students' departmental support via students' computing self-efficacy.

**Figure 2**

*Hypothesized Adaptation of SCCT*



Note. Latent variables are indicated with circles, and rectangles indicate observed variables.

**SCCT’s Personal Inputs and Contextual Influences Applied in Computing**

According to Lent et al. (1994, 2000), the context beyond individual cognition (i.e., self-efficacy, outcome expectations, and personal agency therein) is vital. In fact, one’s perceptions of their context underscore how social and cultural identities, environmental features, and specific learning experiences explain interests and choices related to educational and career aspirations (Lent et al., 2000). Here, personal inputs and contextual influences included: (1) *students’ social and cultural identities* (i.e., race/ethnicity, gender), (2) *mentor support*, (3) *initial self-confidence for graduate admission in computing*, (4) *self-rated math ability*, and (5) *computing departmental support*. By including multiple levels of context (i.e., students’ perceptions of proximal and distal environments), these findings make a significant contribution

to the layered approach of cognitive-person and person-environment variables that SCCT suggests.

First, in broadly evaluating graduate plans, studies have disagreed on the role of gender or race/ethnicity depending on other aspects of students' demographic identities (Perna, 2004; Rocconi et al., 2015). In computing, the gaps in diversity are well documented, but scholars have noted that equity work remains unfinished (e.g., Babeş-Vroman et al., 2018; Beyer, 2014). As such, this study centers the ways in which race/ethnicity and gender underpin educational self-confidence. Second, students' graduate aspirations are often influenced by personal interactions—in particular, those of role models and mentors. SCCT acknowledges role models as contextual affordances (Lent et al., 2000). While mentors may be situated in a variety of environments (e.g., employment, family, education), the present work was expressly interested in students' perceptions of overall mentor support (from any source) during the intro course. I posited that mentor support has a direct relationship with students' computing identity and indirectly affects self-confidence in computing graduate school admission. This hypothesis was rooted in literature on mentorship in computing, which suggests that mentors are key to students' knowledge about educational pathways (Alsharani et al., 2018; Charleston, 2012). Yet, mentorship may not always be positive, and research has documented that USOCC, in particular, may experience negative mentoring interactions (Sullivan et al., 2015).

In addition to individual and relational perceptions, I attended to experiential beliefs via students' initial self-confidence in admission to computing graduate school, self-rated math ability, and departmental support during intro courses (Figure 2). In terms of SCCT's framing, these measures add depth to understanding students' agency via domain-specific predispositions (i.e., initial self-confidence, math self-concept) and how these individual traits may be shaped by

environmental support during the intro course. Using computing-specific variables is a notable extension of this theory's disciplinary applicability, as well. Evidence has suggested that men and white students perceive greater math ability than their peers identifying as women and Students of Color (Rieggle-Crumb et al., 2011), which propelled this inquiry about the influence of self-rated math ability on graduate school pathways across varying groups (i.e., for women, Asian/Asian American students, and USOCC). Finally, I posited that students' perceptions of departmental support during intro computing courses would play an important contextual role in enhancing later computing self-efficacy and self-confidence. Intro courses have been touted as an opportunity to increase self-efficacy (Blaney & Stout, 2017; Wilson & Shrock, 2001) and make computing more accessible for women, USOCC, and non-majors who may be later to learn about computing (Lehman et al., 2020; Margolis & Fisher, 2002). However, what remains to be seen is how early departmental support shapes self-confidence for graduate school admission.

### **Learning Experiences and Computing Self-Efficacy**

On the individual level, Lent et al. (2000) suggested that students' backgrounds are related to interests, choices, and performance via learning experiences, self-efficacy, and outcome expectations (Figure 1). This study's model paralleled SCCT in suggesting that (1) *self-rated academic ability* and (2) *computing self-efficacy* are experiences and expectations that directly relate to students' self-confidence in admission for computing graduate school. Research has importantly supported students' GPAs as a measure of academic ability and predictor of future graduate school behaviors (Eagan et al., 2013; English & Umbach, 2016; Sax, 2001; Xu, 2016). However, GPA is not the only way to measure academic performance. In this vein, scholars have discussed the importance of how students perceive their scholastic competitiveness for graduate school (English & Umbach, 2016). According to Lent et al. (1994), students'

perceived academic ability can be understood as “vicarious learning”—or, the ways individuals determine their personal competence from observing similar others. Given this model’s focus on the nuanced connections between students’ general and disciplinary psychosocial perceptions, I included self-rated academic ability as a measure of vicarious learning experiences.

Self-efficacy—or one’s belief in their ability to successfully master certain skills—is viewed as the theoretical nexus of SCCT, linking learning experiences with individuals’ educational and vocational development (Lent et al., 1994). When it comes to studying the role of affective traits in college trajectories, self-confidence and self-efficacy are well known to shape STEMM educational aspirations (Kyoung Ro et al., 2017; Rottinghaus et al., 2002; Sax et al., 2015). Specifically, scholars have documented how computing self-efficacy may be formed within intro courses (Blaney & Stout, 2017) and explored self-efficacy as a predictor in SCCT-driven models of computing career goals (Sax et al., 2019; Lent et al., 2008, 2011). Related to the outcome of the present study, Litzler et al. (2014) suggested that STEMM confidence varies by personal, environmental, and behavioral factors—including self-efficacy. Despite this recent work, literature remains scant in exploring how computing self-efficacy may be connected to beliefs about computing graduate school. Modeling the relationships between personal, environmental, and behavioral factors predicting students’ self-confidence for computing graduate admission furthers what we know about how intro courses influence computing self-efficacy and later educational pathways.

### **Computing Identity as an Outcome Expectation**

Finally, this study mirrored SCCT (Lent et al., 1994) in directly connecting students’ self-efficacy with outcome expectations. In SCCT, outcome expectations are defined as “personal beliefs about the consequences of performing particular behaviors” (Lent et al., 2000, p. 41) and

are positioned as directly related to learning experiences and self-efficacy expectations. SCCT also proposed that background affordances only indirectly affect outcome expectations, as shown in Figure 1. Here, extending this notion, I hypothesized that *computing identity* could be an outcome expectation and may have a direct relationship with mentoring support during intro courses (Figure 2). Computing identity, or one's sense of feeling like a "computing person," was selected here as a way to highlight a specific type of outcome expectation that Lent et al. (2002) described as "self-directed consequences," which is discussed as intrinsic pride for mastering a certain task (p. 262). Lent et al. (2002) go on to describe how scholars have shown outcome expectations—whether intrinsic (as is the case here) or extrinsic (e.g., tangible rewards)—to play a vital role in motivating career-related behavior, which researchers have also argued to be true of computing identity (Rodriguez & Lehman, 2018).

Evidence has supported the vital role that students' self-assessed computing identity has on later outcomes (e.g., degrees, jobs) and highlighted the ways in which structurally-enforced computing stereotypes may inhibit women and USOCC's development of a computing identity (Cundiff et al., 2013; Kapoor & Gardner-McCune, 2018). Blaney and Stout (2017) also provided evidence supporting the development of computing identity via intro courses—an important connection to make, given this study's view that departmental support during intro courses enhanced computing identity via computing self-efficacy. Taken together, computing identity and computing self-efficacy, alongside perceived academic ability and students' initial levels of self-confidence for graduate admission, were hypothesized as the key variables directly relating to later self-confidence for computing graduate admission.

## **Addressing the Gaps in Prior Research**

While scholars have broadly examined inequities in STEMM graduate school pathways (e.g., Eagan et al., 2013), less attention has been paid to the unique disciplinary contexts of such pathways—especially when it comes to computing fields (Cohoon & Lord, 2007). By focusing on self-confidence for graduate admission in computing, this study considers how individual beliefs and perceptions of support (especially during intro courses) relate to students' confidence for future planned behavior (e.g., gaining graduate school admission). The present work also advances what is known about graduate school trajectories (e.g., aspiration, application, matriculation; see English & Umbach, 2016) by illuminating the place of psychosocial beliefs in these trajectories. Given that self-confidence may be key to leveraging action (via graduate school applications) from students' graduate school aspirations, this is an important contribution.

Building on the foundations of SCCT, the current study also tested relationships among several related—yet distinct—general and disciplinary psychosocial beliefs that might impact students' self-confidence for computing graduate admission (i.e., academic ability, computing self-efficacy, computing identity). By illustrating the connections between such psychosocial beliefs and testing how students' perceptions of support during intro courses shape these beliefs, this study adds a robust perspective about the related and cumulative impact that students' perceived support and abilities have in determining who pursues a graduate degree in computing.

## **Methods**

### **Methodological Approach**

This study employed structural equation modeling (SEM) to investigate how well an adapted version of SCCT fit longitudinal survey data collected at two timepoints from undergraduate students who completed an intro computing course. Using SEM provided the

opportunity to identify direct and indirect relationships and evaluate the extent to which a full model adequately represented the data (Ullman, 2006). Traditionally, SEM takes a confirmatory approach—hence, testing the hypotheses discussed above—and produces observations on multiple variables (Bentler, 1988). Educational researchers’ application of SEM has grown significantly in recent years. Variations of SCCT, particularly relating to STEMM students, have been tested and confirmed using SEM (e.g., Herrera et al., 2011; Lent et al., 2011).

Informed by the SCCT interest model, which is designed to predict individuals’ initial dispositions toward later career and educational goals, this study’s dependent variable was a single-item measure of students’ confidence in getting admitted to a computing graduate program, which ranged from 1 (*strongly disagree*) to 5 (*strongly agree*). Independent variables fit the primary categories of SCCT (Lent et al., 2000) and included: gender, race/ethnicity, perceived mentor support, self-rated math ability, initial self-confidence for computing graduate admission, and perceived departmental support (*personal inputs and contextual influences*); self-rated academic ability (*learning experiences*); computing self-efficacy (*self-efficacy expectations*); and computing identity (*outcome expectations*). Self-rated academic ability was assessed in relation to respondents’ views of the average person their age, whereas computing self-efficacy was measured as self-perceptions; hence, these measures provided different insight to students’ psychosocial development. As previously mentioned, self-efficacy and self-confidence are often confounded, but research has suggested that these constructs are different in that self-efficacy is more attuned to successfully completing specific tasks than self-confidence (Lent, 2016; Lent et al., 1986). Thus, examining associations between each of these traits makes a key contribution in addressing what predicts self-confidence for graduate school admission.

## **Data Source and Sample**

This study used longitudinal data from the BRAID Research project, a mixed-methods study of 15 computing departments at doctoral-granting institutions engaged in diversifying undergraduate computing. The BRAID Initiative, developed by Harvey Mudd College President Dr. Maria Klawe and AnitaB.org, supports these departments' efforts to bolster representation and success for women and Students of Color. A research study of the BRAID Initiative is housed at UCLA and follows two cohorts of students who took an introductory computing course in 2015-2016 (Cohort A) or 2016-2017 (Cohort B). To collect baseline data, the BRAID team administered online surveys to students at the beginning and end of the intro course. To be eligible for annual follow-up surveys, students must have completed a baseline survey. Baseline survey incentives rewarded the first 400 respondents with a \$15 Amazon gift card and entered participants into a raffle to win one of two larger gift cards. Follow-up surveys used guaranteed incentives of \$10 Amazon gift cards provided to each student who completed a survey.

Analyses first used a sample of students from a single cohort (i.e., Cohort A) who took a survey at the end of their intro class (in 2015-2016) and a follow-up survey two years later ( $n = 1,188$ ). This sample was restricted to those who stated graduate aspirations on either survey and indicated an intention to earn their highest degree in computing ( $n = 349$ ), as survey skip logic collected data on respondents' self-confidence in graduate admission only from individuals aspiring to a graduate, non-professional degree in computing. Notably, this sample also included computing majors ( $n = 263$ ) and non-computing majors ( $n = 86$ ), providing key information about how students who completed intro courses, regardless of major during the intro course, anticipated a future in computing. A second cohort of students, who completed an intro course in

2016-2017 and fit the same criteria (i.e., Cohort B), was then used to replicate the structural model. Table 1 provides descriptive statistics of each cohort’s social and cultural identities.

**Table 1**

*Demographic Profile of Student Samples*

	Percentage of students in Cohort A (n = 349)	Percentage of students in Cohort B (n = 352)
<i>Race/ethnicity</i>		
Arab, Middle Eastern, or Persian	2.9	2.3
Asian/Asian American	31.2	34.4
Black or African American	8.6	4.0
Hispanic or Latina/o/x	13.8	8.5
White	34.1	38.6
Two or more: USOCC	5.4	6.3
Two or more: White or Asian/Asian American	3.2	4.5
Other	0.6	1.4
	Percentage of students in Cohort A (n = 347)	Percentage of students in Cohort B (n = 355)
<i>Gender</i>		
Men	66.0	70.4
Women	33.4	29.0
Gender-queer or non-conforming	0.6	0.6
	Percentage of students in Cohort A (n = 344)	Percentage of students in Cohort B (n = 345)
<i>Intersecting identities among gender and race/ethnicity</i>		
White men	25.3	28.4
White women	9.0	10.7
Asian/Asian American men	21.8	25.2
Asian/Asian American women	12.8	14.5
USOCC men	19.2	16.5
USOCC women	11.9	4.6

*Note.* USOCC stands for “underrepresented Students of Color in computing.” American Indian was provided as an option for race/ethnicity, but no American Indian students reported computing graduate aspirations and thus are not included in these samples.

## Measures

The dependent variable for this study was drawn from a follow-up survey item asking students to rate their self-confidence in being admitted to computing graduate school on a five-point scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Latent independent variables of interest included Departmental Support, Mentor Support, Computing Self-Efficacy, and Computing Identity. All of these factors were first tested in SPSS (Version 25) for reliability and further tested as measurement models via confirmatory factor analysis (CFA) in Mplus. Table A2 illustrates the loadings of observed variables in each measurement model.

Departmental Support ( $\alpha = 0.879$ ) was a construct comprised of three observed items on the end-of-introductory-course survey (Time 1), and these items relate to students' perceptions of support from the computing department. The latent construct of Mentor Support ( $\alpha = 0.922$ ) included four observed items and reports the extent to which students felt they had a mentor that could assist with socioemotional, academic, or career-related issues during the intro course (Time 1). Importantly, students could identify multiple types of mentors in the survey; thus, Mentor Support may reflect departmental mentorship (e.g., faculty), industry mentorship (e.g., supervisors), personal mentorship (e.g., parents/guardians), or other forms. Three items from the follow-up survey (Time 2) comprised the Computing Self-Efficacy factor ( $\alpha = 0.752$ ), and these items measured students' self-assessed confidence in mastering computing tasks. Likewise, Computing Identity ( $\alpha = 0.877$ ) included three observed items assessing the extent to which students felt they identified as a "computing person" (Time 2). All factors were assessed on a five-point scale, with Mentor Support ranging from 1 (*not at all*) to 5 (*very much*) and all others ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The correlations for each measurement model, after imputing for missing values, are included in the appendix (Tables A3 – A6).

As intro courses are viewed as a critical juncture of recruitment and retention in computing (Chen, 2013) as well as a key environment to develop self-efficacy and sense of belonging (Blaney & Stout, 2017), this study argues that students' perceptions of departmental support during intro computing courses are also fundamental to students' longer-term educational commitment in computing. However, little is known about the lasting influence of early departmental support on graduate school plans. Computing self-efficacy was also of particular interest, as SCCT posits self-efficacy to be a vital link between one's context, experiences, and later educational or vocational goals (Lent et al., 1994).

Based on prior research, the complexity of relationships among these characteristics, perceptions, and experiences is best modeled via structural equation modeling (SEM). SEM is a quantitative approach that can assess all relationships between independent variables and the associations of independent variables with an outcome concurrently (Ullman & Bentler, 2013). Race/ethnicity, gender, self-rated math ability, self-rated academic ability, and self-confidence in computing graduate admission were the only variables in the model observed directly from the survey; all other items were latent factors, as described above, and tested as measurement models in Mplus. I attempted to create a measurement model for Academic Self-Concept (instead of the single item for academic ability), but this latent construct was too correlated with Computing Self-Efficacy and the outcome to remain in the structural model. Given that SCCT emphasizes the role of self-efficacy, I chose to prioritize this measurement model.

Very few students identified as gender-queer or non-conforming ( $n = 2$ ). As such, I could not include these individuals in inferential analyses and coded gender as a dichotomous variable (0 = man; 1 = woman). Further, given this study's interest in highlighting how the experiences of Asian/Asian American students and USOCC varied from their white peers, race/ethnicity was

recoded into three categorical dummy variables for inferential analyses. Multiracial students who identified with at least one racially/ethnically minoritized group were coded as USOCC; unfortunately, I could not disaggregate the experiences of USOCC due to small sample sizes of individual groups and numerical limitations to parameters in the structural model. Multiracial students who identified as both white and Asian/Asian American were coded as Asian/Asian American-identifying students for inferential analyses. The experiences of Asian and Asian American students in computing are complicated by the fact that they are Students of Color and may have racialized experiences, yet they are numerically well represented in many areas of computing. I recognize this complication and how it informed my racial/ethnic dummy coding. I also know that my positionality as a white researcher creates a lens that diverges from my colleagues of Color. Yet, I care deeply about advancing equity in computing and offer my findings as a contribution to ongoing efforts in the field.

## **Analysis**

### ***Descriptive Statistics***

In order to better understand the sample, I first examined the means and standard deviations for all variables (Appendix, Table A1). The first and second research questions were descriptive in nature, relying on two-way and three-way crosstabulations. These analyses identified important traits among students with high self-confidence in admission for computing graduate school. Further, descriptive analyses allowed me to assess the changes in self-confidence across gender and racial/ethnic groups and across varying levels of self-confidence.

Next, I inspected the data for missingness and normality (Appendix, Table A1). In SPSS, I used multiple imputation (MI) for missing data points, which yields valid statistical inferences, smaller standard errors, and less biased estimates than single imputation methods (Manly &

Wells, 2015). Missing data analysis revealed that all variables had less than 10% missingness, and Little's MCAR test suggested that data were missing at random (Schafer & Graham, 2002). Ten imputations ( $m = 10$ ) were conducted to improve the stability of estimates for missing values, and I imputed values for missing data points across all variables except gender, race/ethnicity, and the dependent variable. Non-respondents to these items ( $n = 8$ ) were removed from the final inferential sample (Cohort A,  $n = 341$ ). I then carried the pooled results over to Mplus. In Mplus, I used the MLM estimation method to acquire robust statistics (i.e., Satorra-Bentler  $\chi^2$ ) and correct for non-normality (Muthén & Muthén, 1998-2017; Satorra & Bentler, 1994).

### ***Multivariate Analysis***

Using Mplus (v8) software, I built four measurement models to test the underlying factors of Departmental Support, Mentor Support, Computing Self-Efficacy, and Computing Identity. With these latent variables, in addition to other observed variables, SEM ("Type = General"; "Estimator = MLM") was then used to trace direct and indirect paths relating to the outcome (Muthén & Muthén, 1998-2017). Correlations for all variables used in structural modeling are provided in the appendix (Table A7). SEM tested whether the adapted SCCT model accurately fit the data reflecting students' self-confidence in being admitted to computing graduate school (Figure 2). Goodness-of-fit indices were used to verify model fit. I relied on Hu and Bentler's (1999) criteria for the comparative fit index (CFI), Tucker-Lewis Index (TLI), and root mean square error of approximation (RMSEA). I also used modification indices (i.e., Lagrange Multiplier and Wald test) to assess if the model was missing or adding parameters detracting from the best conceptual fit (Muthén & Muthén, 1998-2017). Three parameters were added (i.e., math ability and Mentor Support to Departmental Support; math ability to initial self-

confidence) and one parameter was removed (i.e., Mentor Support to Computing Identity) based on these recommendations and an evaluation of their theoretical fit.

Finally, as recommended to verify model fit and add validity to this study's findings (Chin, 1998), SEM analyses were replicated on a second sample (Cohort B, original  $n = 355$ ; inferential  $n = 339$ ). Means and standard deviations for variables in this second cohort are also provided in the appendix (Table A1). As with Cohort A, I conducted MI to impute for missing values ( $m = 10$ ) and removed respondents who did not identify their gender, race/ethnicity, or note their self-confidence in computing graduate school admission on the follow-up survey. After replication, I compared model fit indices (i.e., CFI, TLI, RMSEA) between the two cohorts as well as paths that changed in salience or significance between the cohorts.

### **Limitations**

This study has several limitations. Secondary data are inherently limited, as students may have perceived traits differently and the surveys used were not designed with SCCT in mind; thus, I was limited by the adequacy of available measures. In particular, self-confidence for graduate school admission in computing was measured as a single item—this outcome may be better measured as a latent construct with additional items. Additionally, as confidence for computing graduate school admission was only asked for those reporting computing graduate aspirations on the follow-up survey, the present study was unable to track individuals that may have dropped out of the graduate school pipeline between timepoints.

Second, future quantitative research would benefit from larger samples. Yet, concerns about how the smaller sample size in this study might have affected the validity of results are mitigated by the fact that four measurement models were able to account for error, factor

loadings were relatively high for each of these measurement models, and MI provided robust estimates for missing data points (see Wolf et al., 2013). However, larger and more diverse samples would provide researchers with the means to more critically examine paths for disaggregated racial/ethnic groups and account for further social/cultural identities and family backgrounds. Notably, in testing a parsimonious model that aligned with Lent et al.'s (1994) framework, analyses relied on a limited set of student characteristics and experiential variables, and there are many other salient traits for future research on graduate pathways to consider.

In addition, this sample was also limited to students at 15 doctoral-granting universities, all which self-selected into the BRAID Initiative. Extending this work to institutions that may have different missions or notions of diversity would be useful, and additional research is needed to account for how intro courses and subsequent experiences in computing may be structured at varying institutional types. Despite these limitations, there are many benefits to capturing nuanced relationships among students' experiences in the computing graduate school pipeline, and these findings provide key information for departments seeking to foster greater diversity among students who hold educational aspirations beyond the bachelor's degree.

## **Results**

### **Descriptive Analyses**

The first research question prompted investigation into the social/cultural identities and academic characteristics of students who exhibited high self-confidence in being admitted to graduate school in computing. Although no significant differences emerged across gender, parental education, or SES among students in Cohort A, there remains a need to understand proportional differences across these characteristics. For instance, men reported high self-

confidence in admission to computing graduate school more often than women (Table 2). Also, although no significant differences were found by parent education level, the proportions of students who reported high self-confidence were greater among those with parents that earned a bachelor's degree or higher compared to students whose parents did not have a bachelor's or graduate degree (Table 2). Further, there were significant differences across racial/ethnic identities. Table 2 illustrates that, statistically speaking, a greater proportion of students identifying as white or as Latina/o/x reported high self-confidence in computing graduate admission than their peers identifying as Asian/Asian American.

Next, when addressing the relationship between students' academic backgrounds and high self-confidence for computing graduate admission, results in Table 3 indicate that nearly half of computing graduate aspirants in Cohort A were computer science majors (n = 150). The only significant differences across majors suggested that computer engineering majors were more likely to report high self-confidence than non-STEMM, non-computing majors (47.9% and 8.3%, respectively; Table 3). Interestingly, despite engineering majors being well represented among computing graduate aspirants, only 21.6% of engineering majors indicated high self-confidence in graduate admission. Finally, students with above a 3.5 GPA were more likely to have high self-confidence in computing graduate admission than their peers with lower GPAs.

Looking beyond high self-confidence (i.e., "strongly agree"), the second research question examined how self-confidence levels changed over time and varied by gender and race/ethnicity (Table 4). Although computing graduate aspirants' self-confidence skewed negatively overall, divergent patterns emerged by students' gender and racial/ethnic identities. Most notably, the proportion of women who reported high self-confidence fell from 38.6% to 27.8% over two years, while men's reported levels of high self-confidence increased from 29.8%

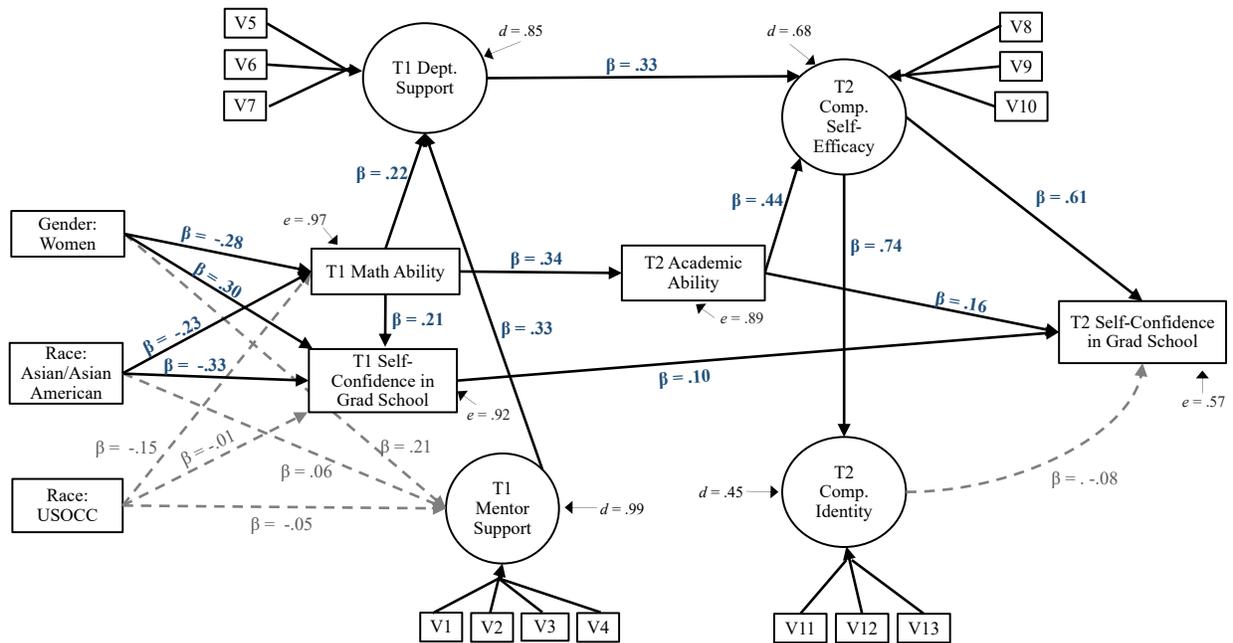
to 34.8%. Further, when looking at those marking “somewhat agree” for their self-confidence in graduate admission, self-confidence among Asian/Asian American students and USOCC seemed to decrease considerably over time. Table 4 shows that the proportion of Asian/Asian American students reporting “somewhat agree” fell from 47.4% to 39.5%, and self-confidence among USOCC reflected a similar drop from 42.6% to 30.8%.

### **Final Structural Model**

Figure 3 displays this study’s final structural model for the first sample (Cohort A), which included four measurement models and presents standardized coefficients for direct paths. In this final model, 42.7% of the variance in students’ self-confidence for computing graduate school admission was explained. According to Hu and Bentler’s (1999) established cutoff values (good fit indicated by CFI > 0.95, TLI > 0.95, and RMSEA < .06), the final model’s fit indices reveal that these data fit well with the adjusted model (CFI = 0.951, TLI = 0.940, RMSEA = 0.052). The Chi-square statistic was not used in evaluating model fit, due to scholars’ concerns of this statistic’s dependence on sample size and normality of data (Hooper et al., 2008). All parameter estimates shown with solid lines in Figure 3 were significant at the 0.05 level or below, with many being significant at the 0.001 level. The paths shown with dotted lines were not significant in the final model; however, they remained in the model for their theoretical importance to this study.

**Figure 3**

*Final Structural Model for Cohort A*



*Note.* Final structural model for Cohort A, with measurement variables shown, for the relationships that predict students' self-confidence in being admitted to graduate school in computing ( $n = 341$ ).  $\chi^2/df = 16.1$ , CFI = 0.951, TLI = 0.940, RMSEA = 0.052.

Table 5 clarifies all total direct and indirect paths between independent variables and the dependent variable. The latent variable of Computing Self-Efficacy had the strongest significant direct path to self-confidence ( $\beta = 0.608$ ), which suggests that students with higher Computing Self-Efficacy also reported higher self-confidence in being admitted to computing graduate school, net of control variables. There was also an indirect path for Computing Self-Efficacy via Computing Identity (the hypothesized outcome expectation in this adaptation of SCCT), but all paths traced through the factor for Computing Identity were statistically non-significant. This non-significance was of particular interest, as I hypothesized that those who felt like “computing

people” may be more likely to have high self-confidence for admission to computing graduate school. However, this does not appear to be the case.

A second direct effect on the outcome can be seen by examining the role of students’ self-confidence in being admitted to computing graduate school at the end of the intro course ( $\beta = 0.108$ ). Although not surprising that students’ earlier self-confidence significantly predicted later self-confidence, it is surprising that this pre-test measure did not play a larger role. The only other direct effect predicting self-confidence was students’ self-rated academic ability ( $\beta = 0.155$ ). This significant effect suggests that, net of control variables, students with higher self-rated academic ability two years after the intro course also had higher self-confidence in admission to a computing graduate program. In addition, the indirect effect of academic ability to self-confidence in graduate admission via Computing Self-Efficacy ( $\beta = 0.303$ ) suggests that, once other variables in the model were accounted for, students’ academic ability was a stronger predictor of self-confidence in getting admitted to computing graduate school when students also felt that they were equipped to successfully complete computing-related tasks.

In terms of students’ perceived departmental support during intro courses, the significant indirect effect in Table 5 ( $\beta = 0.246$ ) suggests that, when controlling for other variables, the effect of the Departmental Support factor on self-confidence for graduate admission was mediated by Computing Self-Efficacy two years after students’ intro course. That is to say, a supportive computing environment was most important to students’ self-confidence in graduate admission if departments also cultivated self-efficacy in computing. Likewise, one indirect effect tracing the relationship of the construct for Mentor Support during intro courses to later self-confidence was significant, albeit a smaller effect ( $\beta = 0.060$ ). This suggests that, net of control

variables, the role of mentorship during an intro course on later self-confidence for graduate admission was mediated by both departmental support and computing self-efficacy.

Through indirect relationships, students' self-rated math ability during the intro course was also significantly related to self-confidence for computing graduate admission ( $\beta = 0.213$ ). Several indirect paths contributed to this; namely, self-rated academic ability, Computing Self-Efficacy, and Departmental Support all illuminated the lasting effect that early perceptions of math ability can have on later self-confidence for graduate school admission. The strongest indirect effect between self-rated math ability and later self-confidence, net of other variables, was that which traced math ability through perceived academic ability and the Computing Self-Efficacy construct ( $\beta = 0.099$ ). This again suggests that students' disciplinary confidence in successfully doing computing tasks is key.

When assessing gender differences, two sets of indirect paths from gender to self-confidence (two years after the intro course) were significant ( $p < 0.05$ ). One set of paths via math ability and academic ability ( $\beta = -0.014$ ) and a second set of paths via math ability, academic ability, and Computing Self-Efficacy ( $\beta = -0.025$ ) suggested that women had lower self-confidence in computing graduate admission than men. The negative direct effect seen between gender and math ability during the intro course ( $\beta = -0.276$ ) appears to have played a lasting role in these indirect paths. Further descriptive investigation uncovered that there were no significant differences in departmental support during the intro course by gender. However, additional analyses found that men and women's perceptions of math ability did change over time in different ways. The proportion of women rating their math ability in the highest 10% relative to the average person their age dropped from 21.9% ( $n = 25$ ) to 13.8% ( $n = 16$ ). In

contrast, men's self-rated math ability in this top echelon stayed constant at 24% (n = 55) at the end of the intro course and 24.9% (n = 57) two years later.

Additionally, total indirect effects for Asian and Asian American students ( $\beta = -0.073$ ) suggest that students identifying as Asian/Asian American had lower self-confidence in computing graduate admission than their white peers. It is worth noting that Asian/Asian American students' lower perceptions of their math ability ( $\beta = -0.209$ ) and self-confidence for graduate admission ( $\beta = -0.293$ ) during intro courses likely played a key role in these negative paths. Further, although not statistically significant, it is both noteworthy and concerning that USOCC seem to have negative mentoring relationships in their intro courses ( $\beta = -0.052$ ). This suggests that not all mentorship may be helpful mentorship, depending on students' identities.

### **Replication of Final Structural Model**

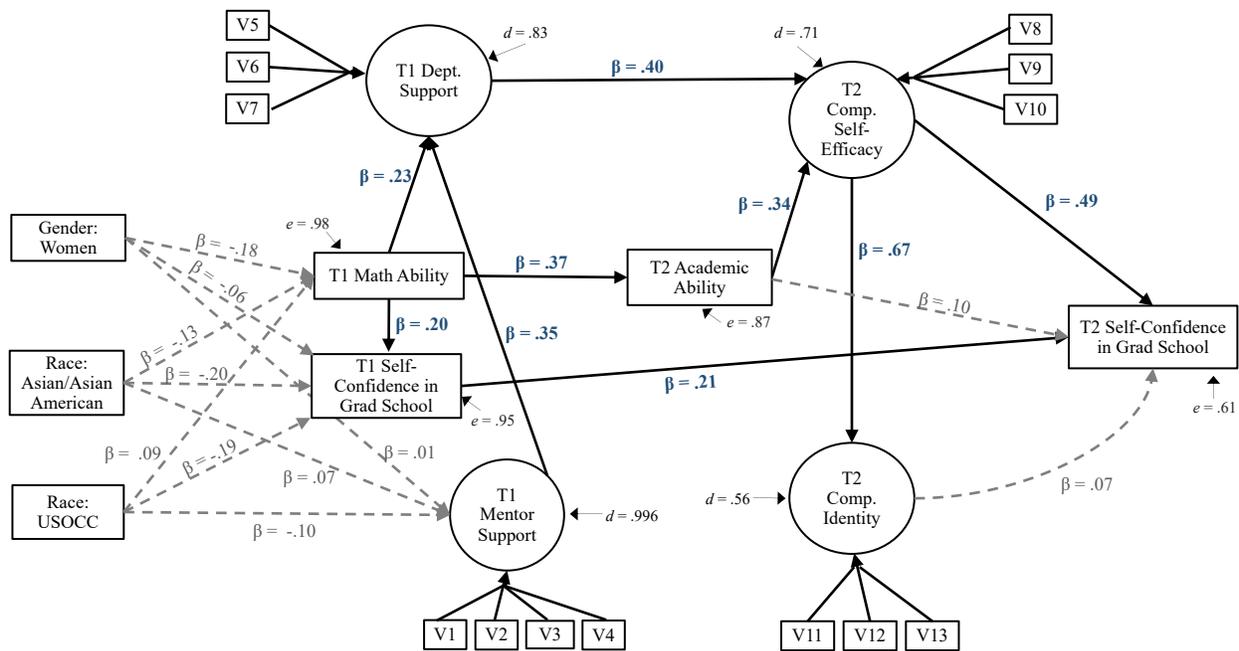
To validate this study's final structural model, I employed the analyses above on Cohort B, who took an intro course in 2016-2017 (Figure 4). The model fit indices for this replication indicated that the adjusted model did not fit these data as well as the first cohort (CFI = 0.912, TLI = 0.893, RMSEA = 0.067). For Cohort B, this SEM model predicted 38.6% of the variance in students' self-confidence for graduate school admission in computing, compared to the 42.7% of variance explained in Cohort A. It may be the case that some of these differences in model fit are due to differences in the samples themselves, as computing graduate aspirants in Cohort B are less diverse than Cohort A (see Table 1).

In exploring the similarities and differences in model fit between cohorts, some interesting differences emerged across students' social and cultural identities. No demographic identity paths were direct or indirect predictors of self-confidence for graduate school admission in Cohort B, which runs contrary to the findings of Cohort A. Despite these shifts, results from

Cohort B confirmed the importance of Computing Self-Efficacy ( $\beta = 0.486$ ) and provided evidence to suggest that students' initial beliefs in their ability to be admitted to graduate school during the intro course may be more important than findings from Cohort A suggested ( $\beta = 0.211$ ).

**Figure 4**

*Final Structural Model for Cohort B*



*Note.* Final structural model for Cohort A, with measurement variables shown, for the relationships that predict students' self-confidence in being admitted to graduate school in computing ( $n = 341$ ).  $\chi^2/df = 16.1$ , CFI = 0.951, TLI = 0.940, RMSEA = 0.052.

## Discussion

This study examined the extent to which students' psychosocial beliefs and perceptions of intro course support shape students' self-confidence for computing graduate school admission, focusing on variation by students' gender and race/ethnicity. The present work makes a key

contribution to research on STEMM graduate pathways by investigating the role of students' perceived departmental and mentor support during intro courses, highlighting the interplay between different psychosocial factors (i.e., academic ability, self-efficacy, and confidence for graduate admission), and focusing on computing as a unique discipline in STEMM.

From these results, several key takeaways are important to bear in mind about students' self-confidence for computing graduate school admission. First, inequities in self-confidence for graduate admission and math self-concept are notably present in intro courses. While women reported higher levels of self-confidence than men during the intro course, women appeared to have lower levels of math self-concept in intro courses than their peers who were men. Results also showed that Students of Color reported lower levels of self-confidence and math self-concept than their white peers in the intro course. Second, over two years in college, it appears that self-confidence levels are quite malleable among computing graduate aspirants—providing reason to believe that there are many opportunities for institutions to impact students' confidence. Finally, these results suggest that departments should closely consider interventions that bolster computing self-efficacy, as a strong sense of disciplinary self-efficacy seems to have strong ties with self-confidence for admission to graduate school in computing.

As hypothesized, results largely indicate that there are gender and racial/ethnic inequities in self-confidence for computing graduate admission. While Lent et al. (1994, 2000) also outlined how individuals' social and cultural identities might shape their trajectories, the methodological approach in this study adds clarity to how gender and race/ethnicity might moderate students' self-confidence. While self-confidence appears to be fairly constant for men over time, the fluctuation among self-confidence levels for women and Students of Color is concerning.

Initially, women had higher self-confidence than men during the intro course. But, women reported noticeably lower levels of self-confidence than men two years after the intro course. Because women enroll in STEMM graduate programs at lower rates than men (Sax, 2001; Szelényi & Inkelas, 2011), some may say that women’s lower self-confidence might help explain this underrepresentation. However, it may also be that the dominant narrative that men are “good” at computing prompts men to be overconfident in their abilities. Further, women’s later self-confidence seems to be negatively impacted by math self-concept during intro courses, which suggests that women’s early perceptions of their abilities are powerful. Despite post-hoc analyses revealing that women’s math self-concept improved slightly throughout college<sup>4</sup>, a gender gap remained and contributed to larger gender gaps in self-confidence for graduate admission. This supports existing literature that discusses the negative long-term effects of women’s lower math self-concept (e.g., Riegle-Crumb et al., 2011; Sax et al., 2015). Further, this also suggests that much remains to be done to provide structures that foster women’s earlier math self-concept during intro courses and in their K-12 experiences.

In computing, researchers have often treated white and Asian/Asian American students as a single “majority” group due to both groups being numerically well represented in the field. In this study, I disaggregated white and Asian/Asian American students’ experiences to highlight the ways in which Asian and Asian American students have different experiences than their white peers in the computing graduate pipeline. Findings suggest that Asian/Asian American students have lower intro course math self-concept and self-confidence (at both timepoints) than their white peers. This suggests that the culture of undergraduate computing is more racialized

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<sup>4</sup> Bivariate correlations revealed a negative association of  $-0.130$  between gender and initial self-rated math ability (Time 1), whereas the association between gender and math ability at Time 2 was  $-0.122$ .

than previously captured by studies that aggregate white and Asian/Asian American students into a majority group. Rather, environments may be steeped in whiteness, thus privileging white students to report higher levels of confidence in their abilities than their peers of Color. Much remains to be explored as to why Asian and Asian American students appear to report lower self-confidence for computing graduate school and what institutions can do to support this self-confidence. While SCCT may not directly aid interpretation of these important results, future research should use a more critical theory to explore if and how these findings may support the vital work being done to debunk the model minority myth (Poon et al., 2016; Trytten et al., 2012) and do so in the context of computing.

In addition, I hypothesized that students' computing self-efficacy would play a salient role in enhancing self-confidence for graduate admission. Computing self-efficacy served to mediate and strengthen the influence of several other cognitive perceptions (e.g., departmental support, self-rated academic ability). For example, high self-ratings of academic ability enhanced students' confidence for graduate admission—which supports the known role of academic ability in graduate plans (English & Umbach, 2016)—but, this effect was even stronger when students also reported high levels of computing self-efficacy. Likewise, students' perceptions of departmental support appeared to directly relate to computing self-efficacy, which adds to Blaney and Stout's (2017) work linking intro course experiences to the formation of self-efficacy in computing. The critical role that computing self-efficacy plays in this study has meaningful implications for future applications of SCCT. As a theoretical approach, Lent et al. (1994, 2000) posited self-efficacy as a general measure of individuals' perceived ability to do certain tasks. Other studies, such as one by Byars-Winston & Fouad (2008), have tested more specific forms of self-efficacy (i.e., math/science self-efficacy) through SEM. This study's findings suggest an

even more specific form of disciplinary self-efficacy as integral to graduate school trajectories, which is logical given that graduate school requires increasing disciplinary specialization.

Aligning with SCCT, I also hypothesized that computing self-efficacy would directly and positively relate to computing identity (i.e., outcome expectations) and that both factors would directly predict self-confidence for graduate admission. While findings do uphold the link between self-efficacy and outcome expectations, students' identity as a "computing person" was not a significant predictor of their confidence for graduate admission. In addition, the coefficient between students' computing identity and their self-confidence for graduate admission was negative, which contrasts existing evidence on the importance of science identity to STEMM graduate school plans (Merolla & Serpe, 2013). Further, students' support from mentors during intro courses was not a significant predictor of computing identity; thus, this path was removed from the model, despite research supporting the ways in which mentors affect computing identity and sustained commitment to computing (Alsharani et al., 2018; Charleston, 2012).

Largely, the tenability of this structural model and descriptive findings confirm the conceptual importance of *triadic reciprocity* in Bandura's (1986) social cognitive theory, which emphasizes that personal attributes, external environmental factors, and overt behavior all work collaboratively to impact self-referent thinking. The interconnected nature of varying contexts with cognition and behavior is essential to consider when investigating disparities in self-confidence for computing graduate admission, and the results of this study provide important evidence to make inroads toward diversifying the computing graduate school pipeline.

## **Implications**

### **Implications for Research**

These results point to several important directions for future research. Beyond what is captured in the present study, there are likely other individual traits, collegiate experiences, and interactions that shape students' self-confidence for graduate admission. Future research should consider focusing on some of these, such as family backgrounds (e.g., parental education, SES), classroom interactions, formal research experiences, or specific types of mentorship (e.g., emotional support, career support). Studies of graduate school pathways would also benefit from separately examining master's and doctoral levels of study. Also, inferential analyses were not able to account for specific USOCC groups or intersecting identities (e.g., Women of Color) due to limited sample sizes, and this is critical for future work. Research about computing graduate pathways needs to examine the specific ways marginalization occurs and how interlocking systems of oppression (e.g., racism, sexism) may paint a different picture of post-baccalaureate aspirations. Finally, research would benefit from longitudinal data that account for how students' confidence for graduate admission informs behavior (e.g., application and matriculation) and graduate school experiences (which might be explored via SCCT's choice and performance models).

### **Implications for Theory**

Given that this study tested SCCT's applicability to graduate school trajectories in a computing context, results offer important theoretical implications for scholars to consider. First, researchers using SCCT to examine educational or career pathways in specific fields would be wise to use a disciplinary-specific measure of self-efficacy (e.g., computing self-efficacy). From these results, I suspect that using more precise, domain-specific measures of self-efficacy would

continue to yield more contextually relevant results in other studies. In addition, although SCCT posits that contextual environments are key to individuals' educational and vocational development, using this theory alone does not account for how social interactions may be laced with structures of power. For instance, students' definitions of departmental support might vary depending on the dynamics at play. Hence, studies should consider using social psychological theory (e.g., structural symbolic interactionism, expectation states theory) or critical approaches (e.g., feminist standpoint theory, intersectionality) to help explain larger systemic inequities.

### **Implications for Practice**

In terms of practical implications, computing faculty and administrators may find these results especially useful. In light of how salient students' perceptions during intro courses are to later self-confidence for graduate school admission, faculty—and perhaps graduate admissions professionals (see Wofford, 2019)—need to introduce the concept of graduate school early. If departmental leaders can create equitable ways to develop *and sustain* students' self-confidence for graduate school admission in computing—particularly that of women and Students of Color—computing graduate programs may see increased diversity in their application pools. In this study, the low confidence levels among women and Students of Color (and the decrease in their reported confidence levels over two years) suggest that there may be cultural and structural issues in computing that uphold inequities. Thus, departments should also consider attending to practices that may negatively affect self-confidence for graduate admission, such as the negative mentoring support that USOCC may perceive in their intro courses. Departmental leaders might be able to make a difference in these negative perceptions by developing training for individuals who serve as mentors and ensuring that mentors intentionally affirm students' social and cultural identities (see NASEM, 2019).

Further, these results indicate that computing self-efficacy has a strong, positive role in enhancing self-confidence for graduate admission in the two years following an intro course. As such, computing faculty should ensure that there are institutionalized opportunities (e.g., intentionally implementing pair programming, hosting a technical symposium) for students to develop proficiency and confidence in computing skills. Importantly, despite community college students not being a primary focus of this study, a quarter of graduate aspirants in the first cohort had attended community college. Thus, it is probable that students' computing self-efficacy is affected by experiences beyond the four-year setting. It may be beneficial to create specific opportunities for upward transfer students to develop computing self-efficacy. For example, computing leaders at four-year universities could organize a community college alumni research symposium, allowing upward transfer students to prepare and showcase their research to students and faculty at local community colleges. Departmental leaders at community colleges could replicate this, such that current community college students have the opportunity to present their research at nearby four-year institutions and gain confidence in their computing skills.

### **Implications for Policy**

These findings also point to ways that institutional policies might shape students' self-confidence. First, it would behoove computing departments to follow the lead of K-12 efforts in cultivating policy for computing pathways. For example, the Alliance for California Computing Education for Students and Schools (n.d.) has several taskforces working to ensure that state resources are allocated to provide quality K-12 computer science education and strengthen equitable opportunities for K-12 students preparing for college. Similarly, undergraduate computing departments could consider building taskforces to advocate for state resources that might be used to bolster the undergraduate to graduate school pipeline, with a particular focus on

how to cultivate greater diversity. Also, departments should evaluate their graduate admissions criteria with an eye toward equity. For example, as undergraduate students' confidence for graduate admission may be affected by their perceptions of the GRE, one consideration may include removing the GRE requirement—following a national trend where institutional leaders are removing the GRE in an effort to increase equitable access to graduate school (Langin, 2019). Finally, at a national level, the NSF Computer and Information Science and Engineering (CISE) directorate now strongly encourages grant submissions to provide evidence of broadening participation in computing (Kurose, 2017). As an extension, CISE program officers may consider recommending that new projects emphasize increasing computing self-efficacy among minoritized populations (perhaps through technical symposiums, as mentioned), given that computing self-efficacy plays a salient role in students' confidence within their graduate school pathways.

### **Conclusion**

This study examines how—and which—students develop self-confidence for graduate school admission in computing, as a unique subset of STEMM fields that are faced with both a need (a shortage of diverse faculty) and opportunity (booming undergraduate enrollments) to improve equity in the graduate school pipeline. Notably, testing the applicability of social cognitive career theory to examine students' self-confidence for computing graduate school admission illuminates the key role of early beliefs and forms of support in intro courses as well as the importance of computing self-efficacy. Given the salient role of students' perceptions of their own abilities and of their environmental support, it is apparent that simply having graduate school aspirations may not be enough to cultivate greater diversity in computing graduate school. As such, undergraduate computing departments need to pay close attention to how departmental

environments impact students' affective beliefs, thus sustaining or disrupting students' self-confidence in computing graduate school admission, shaping who goes on to graduate school, and potentially affecting who fills the faculty shortage in the computing field.

## Tables

**Table 2**

*Demographic Traits of Students with High Self-Confidence in Being Admitted to Computing Graduate School, Two Years After an Intro Computing Course (n = 349)*

Demographic Background	% Within Group that "Strongly Agree"	Sig. Diff. From
<b>Gender</b>		
Men (n = 227)	34.8	
Women (n = 115)	27.8	
<b>Race/Ethnicity, by Group</b>		
(1) White or Caucasian (n = 118)	39.0	2
(2) Asian/Asian American (n = 108)	19.4	1, 4
(3) Black or African American (n = 30)	16.7	
(4) Hispanic or Latina/o/x (n = 48)	50.0	2
(5) Native Hawaiian or Pacific Islander (n = 1)	100.0	
(6) Arab, Middle Eastern, or Persian (n = 9)	33.3	
(7) Two or more: USOCC (n = 19)	47.4	
(8) Two or more: White or Asian/Asian American (n = 11)	27.3	
(9) Other (n = 2)	100.0	
<b>Parents' Highest Education Level</b>		
High school or less (n = 49)	28.6	
Some college or associate's degree (n = 40)	15.0	
Bachelor's degree (n = 86)	39.5	
Graduate or professional degree (n = 115)	36.5	
<b>Socioeconomic Status</b>		
Poor (n = 15)	3.6	
Below average (n = 55)	13.0	
Average (n = 141)	44.0	
Above average (n = 86)	35.0	
Wealthy (n = 10)	4.0	

*Note.* Significant differences indicate differences among column proportions at  $p < .05$ . USOCC stands for "underrepresented Students of Color in computing." American Indian was provided as an option for race/ethnicity, but no American Indian students reported computing graduate aspirations and thus are not included in these samples.

**Table 3**

*Proportional Comparison of the Academic Traits of Students with High Self-Confidence in Being Admitted to Computing Graduate School, Two Years After an Intro Computing Course (n = 349)*

Academic Background	% Within Group that "Strongly Agree"	Sig. Diff. From
<b>Major</b>		
(1) Computer science (n = 150)	36.7	
(2) Computer information systems (n = 20)	30.0	
(3) Computing and business (n = 9)	44.4	
(4) Information technology (n = 26)	23.1	
(5) Computer engineering (n = 48)	47.9	8
(6) Engineering (n = 37)	21.6	
(7) Other STEM (n = 24)	33.3	
(8) Non-STEM, non-computing (n = 24)	8.3	5
<b>Community College Attendance (n = 76)</b>	25.7	
<b>Highest Degree Aspiration</b>		
Master's degree (n = 276)	32.6	
Ph.D. or Ed.D. degree (n = 70)	34.3	
<b>College GPA (4.0 scale)</b>		
(1) Below 3.0 GPA (n = 42)	9.5	3
(2) Between 3.0 and 3.5 GPA (n = 92)	20.7	3
(3) Above 3.5 GPA (n = 133)	52.3	1, 2

*Note.* Bioinformatics (n = 1) or Other Computing (n = 1) majors are not shown due to small sample size and neither student indicating "strongly agree." Significant differences indicate differences among column proportions at  $p < .05$ .

**Table 4**

*Proportional Changes in Students' Self-Confidence in Being Admitted to Computing Graduate School from their Introductory Computing Course to Two Years Later (Cohort A)*

Agreement with Self-Confidence in Admission	% Among All	% Among Gender		% Among Race/Ethnicity		
		Men (T1 n = 218; T2 n = 227)	Women (T1 n = 114; T2 n = 115)	White (T1 n = 116; T2 n = 118)	Asian/Asian American (T1 n = 116; T2 n = 119)	USOCC (T1 n = 101; T2 n = 107)
<b>Strongly Disagree</b>						
Time 1	1.8	1.8	1.8	2.6	1.7	1.0
Time 2	2.0	2.6	0.9	0.0	2.5	3.7
<b>Somewhat Disagree</b>						
Time 1	2.4	1.8	3.5	0.9	4.3	2.0
Time 2	7.2	7.5	7.0	4.2	10.9	6.5
<b>Neither Agree nor Disagree</b>						
Time 1	22.1	27.1	13.2	21.6	26.7	17.8
Time 2	22.3	21.1	25.2	20.3	26.9	19.6
<b>Somewhat Agree</b>						
Time 1	41.2	39.4	43.0	33.6	47.4	42.6
Time 2	35.5	33.9	39.1	36.4	39.5	30.8
<b>Strongly Agree</b>						
Time 1	32.5	29.8	38.6	41.4	19.8	36.6
Time 2	32.9	34.8	27.8	39.0	20.2	39.3

**Table 5**

*Summary of Direct and Indirect Effects of Final Structural Model for the Relationships Predicting Students' Self-Confidence in Being Admitted to Graduate School in Computing (Cohort A; n = 341)*

Variables	Direct effects ( $\beta$ )	Indirect effects ( $\beta$ )
Gender: Women		-.012
Race/Ethnicity: Asian/Asian American		-.073*
Race/Ethnicity: USOCC		-.032
Self-confidence in admission to computing graduate school (pre-test)	.108*	
Self-rated math ability		.213***
Mentor Support		.060***
Departmental Support		.246***
Self-rated academic ability	.155**	.303***
Computing Self-Efficacy	.608***	-.075
Computing Identity	-.076	

*Note.* \*  $p < .05$ ; \*\*  $p < .01$ ; \*\*\*  $p < .001$ .

## Appendix

**Table A1**

*Descriptive Statistics on Key Characteristics*

Variable	Cohort A (n = 349)			Cohort B (n = 355)			<i>(Min, Max)</i>
	<i>M</i>	<i>SD</i>	<i>% Missing</i>	<i>M</i>	<i>SD</i>	<i>% Missing</i>	
<b>Dependent Variable</b>							
Self-confidence for computing graduate admission (Time 2)	3.90	1.008	0.9	3.85	0.949	1.7	1, 5
<b>Independent Variables</b>							
<i>Self-Confidence for Computing Graduate Admission (Time 1)</i>	4.00	0.897	4.0	3.94	0.913	2.5	1, 5
<i>Self-Rated Math Ability (Time 1)</i>	3.83	0.864	4.0	3.78	0.867	3.1	1, 5
<i>Mentor Support (Time 1)</i>							
A mentor...							
Helps me improve my computing skills	2.83	1.386	8.0	2.75	1.318	2.5	1, 5
Shows compassion for concerns and feelings I share with them	3.09	1.391	8.0	3.01	1.281	2.3	1, 5
Shares personal experiences as an alternative perspective to my problems	3.02	1.427	8.0	2.89	1.304	2.5	1, 5
Explores career options with me	2.90	1.428	9.2	2.72	1.317	2.5	1, 5
<i>Departmental Support (Time 1)</i>							
I feel a sense of community in the computing dept.	3.70	0.943	4.3	3.69	0.945	3.1	1, 5
The dept. cares about its students	3.92	0.897	4.6	3.90	0.870	3.4	1, 5
The environment in the computing dept. inspires me to do the best job that I can	3.73	0.970	4.3	3.79	0.928	2.8	1, 5
<i>Self-Rated Academic Ability (Time 2)</i>	3.90	0.794	0.0	3.91	0.806	0.8	1, 5
<i>Computing Self-Efficacy (Time 2)</i>							
If I pursue computing, I am confident that I can...							
Become a leader in the field of computing	3.36	1.068	0.9	3.26	1.049	0.8	1, 5
Quickly learn a new programming language on my own	3.97	0.902	1.4	3.95	1.010	0.8	1, 5
Clearly communicate technical problems and solutions to a range of audiences	3.88	0.898	0.9	3.89	0.912	0.8	1, 5
<i>Computing Identity (Time 2)</i>							
I see myself as a "computing person"	3.97	0.939	0.0	4.02	0.948	1.1	1, 5
I feel like I "belong" in computing	3.82	1.049	0.6	3.85	1.062	1.4	1, 5
Computing is a big part of who I am	3.77	1.050	0.9	3.74	1.077	1.4	1, 5

**Table A2***Loadings of Observed Variables in Measurement Models (Cohort A; n = 341)*

Variable	Std. Loading
<b>Mentor Support</b> ( <i>Time 1; Cronbach's alpha = .922</i> )	
A mentor helps you improve your computing skills <sup>1</sup>	0.659
A mentor shows compassion for any concerns and feelings you discussed with them <sup>1</sup>	0.937
A mentor shares personal experiences as an alternative perspective to your problems <sup>1</sup>	0.935
A mentor explores career options with you <sup>1</sup>	0.620
<b>Departmental Support</b> ( <i>Time 1; Cronbach's alpha = .879</i> )	
I feel a sense of community in the computing dept. <sup>2</sup>	0.799
The dept. cares about its students <sup>2</sup>	0.824
The environment in the computing dept. inspires me to do the best job that I can <sup>2</sup>	0.890
<b>Computing Self-Efficacy</b> ( <i>Time 2; Cronbach's alpha = .752</i> )	
I am confident that I can become a leader in the field of computing <sup>2</sup>	0.699
I am confident that I can quickly learn a new programming language on my own <sup>2</sup>	0.721
I am confident that I can clearly communicate technical problems and solutions to a range of audiences <sup>2</sup>	0.678
<b>Computing Identity</b> ( <i>Time 2; Cronbach's alpha = .877</i> )	
I see myself as a 'computing person' <sup>2</sup>	0.855
Computing is a big part of who I am <sup>2</sup>	0.667
I feel like I "belong" in computing <sup>2</sup>	0.904

<sup>1</sup> Five-point scale: 1 = "not at all" to 5 = "very much".<sup>2</sup> Five-point scale: 1 = "strongly disagree" to 5 = "strongly agree".

**Table A3***Correlations Among Observed Variables for Mentor Support (Cohort A; n = 341)*

Variable	M	SD	1	2	3	4
V1. A mentor helps you improve your computing skills	2.82	1.371	—			
V2. A mentor shows compassion for any concerns and feelings you discussed with them	3.08	1.377	.711*	—		
V3. A mentor shares personal experiences as an alternative perspective to your problems	3.01	1.416	.673*	.879*	—	
V4. A mentor explores career options with you	2.87	1.416	.671*	.760*	.774*	—

Note. \*  $p < .01$ ; all two-tailed. Values reflect full dataset after  $m = 10$  imputations.

**Table A4***Correlations Among Observed Variables for Students' Departmental Support (Cohort A; n = 341)*

Variable	M	SD	1	2	3
V5. I feel a sense of community in the computing dept.	3.70	.925	—		
V6. The dept. cares about its students	3.93	.887	.659*	—	
V7. The environment in the computing dept. inspires me to do the best job that I can	3.74	.964	.709*	.735*	—

Note. \*  $p < .01$ ; all two-tailed. Values reflect full dataset after  $m = 10$  imputations.

**Table A5***Correlations Among Observed Variables for Computing Self-Efficacy (Cohort A; n = 341)*

Variable	M	SD	1	2	3
V8. Confidence to become a leader in the field of computing	3.36	1.066	—		
V9. Confidence to quickly learn a new programming language on my own	3.97	.899	.500*	—	
V10. Confidence to clearly communicate technical problems and solutions to a range of audiences	3.87	.892	.481*	.517*	—

Note. \*  $p < .01$ ; all two-tailed. Values reflect full dataset after  $m = 10$  imputations.

**Table A6***Correlations Among Observed Variables for Computing Identity (Cohort A; n = 341)*

Variable	M	SD	1	2	3
V11. I see myself as a 'computing person'	3.96	.938	—		
V12. Computing is a big part of who I am	3.77	1.051	.644*	—	
V13. I feel like I “belong” in computing	3.82	1.047	.781*	.692*	—

Note. \*  $p < .01$ ; all two-tailed. Values reflect full dataset after  $m = 10$  imputations.

**Table A7***Correlations Among All Variables Used in Structural Equation Modeling Analyses (Cohort A; n = 341)*

Variable	1	2	3	4	5	6	7	8	9	10	11
1. Outcome: Confidence for computing graduate admission	—										
2. Gender: Women	-.020	—									
3. Race/Ethnicity: Asian/Asian American	-.183**	.042	—								
4. Race/Ethnicity: USOCC	.037	.070	-.489**	—							
5. Initial confidence for computing graduate admission	.284**	.099	-.159**	.087	—						
6. Self-rated math ability	.189**	-.125*	-.085	-.051	.232**	—					
7. Mentor Support (Factor)	.081	.095	.040	-.032	.045	.096	—				
8. Departmental Support (Factor)	.191**	-.001	.001	-.020	.317**	.227**	.317**	—			
9. Self-rated academic ability	.425**	-.075	-.166**	-.044	.129*	.383**	.038	.118*	—		
10. Computing Self- Efficacy (Factor)	.563**	-.068	-.191**	.109*	.296**	.259**	.103	.275**	.410**	—	
11. Computing Identity (Factor)	.428**	-.170**	-.087	-.009	.260**	.164**	.130*	.345**	.328**	.596**	—

*Note.* \* $p < .05$  and \*\* $p < .01$ ; all two-tailed. Factors here were constructed in SPSS for the purpose of providing correlations. Values reflect full dataset after  $m = 10$  imputations.

## References

- Alliance for California Computing Education for Students and Schools (n.d.). *About ACCESS*.  
<https://access-ca.org/about>
- Alsharani, A., Ross, I., & Wood, M. I. (2018). Using social cognitive career theory to understand why students choose to study computer science. In *Proceedings of the ACM ICER Conference on International Computing Education Research*, 205-214.
- Babeş-Vroman, M., Tjang, A., & Nguyen, T. (2018). *Examining race/ethnicity diversity in the enrollment of a 4-year CS university program* (Technical Report).  
<https://doi.org/10.7282/T3QN69ZQ>
- Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, 84(2), 191-215.
- Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice Hall.
- Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman and Company.
- Bentler, P. M. (1988). Causal modeling via structural equation systems. In J. R. Nesselrode & R. B. Cattell (Eds.), *Handbook of multivariate experimental psychology* (2<sup>nd</sup> ed., pp. 317-335). Plenum.
- Beyer, S. (2014). Why are women so underrepresented in computer science? Gender differences in stereotypes, self-efficacy, values, and interests and predictors of future CS course-taking and grades. *Computer Science Education*, 24(2-3), 153-192.  
<https://doi.org/10.1080/08993408.2014.963363>
- Blaney, J. M., & Stout, J. G. (2017). Examining the relationship between introductory computing course experiences, self-efficacy, and belonging among first-generation college women. In *Proceedings of the 48<sup>th</sup> ACM SIGCSE Technical Symposium on Computer Science Education (SIGCSE '17)*, 69-74.
- Byars-Winston, A. M., & Fouad, N. A. (2008). Math and science social cognitive variables in college students: Contributions of contextual factors in predicting goals. *Journal of Career Assessment*, 16(4), 425-440.
- Charleston, L. J. (2012). A qualitative investigation of African Americans' decision to pursue computing science degrees: Implications for cultivating career choice and aspiration. *Journal of Diversity in Higher Education*, 5(4), 222-243.  
<https://doi.org/10.1037/a0028918>
- Chen, X. (2013). STEM attrition: College students' paths into and out of STEM fields. Statistical Analysis Report. NCES 2014-001. *National Center for Education Statistics*.

- Chin, W. W. (1998). Commentary: Issues and opinion on structural equation modeling. *MIS Quarterly*, 2(1), vii-xvi.
- Cohoon, J. M., & Lord, H. (2007). Women's entry to graduate study in computer science and computer engineering in the United States. In C. J. Burger, E. G. Creamer, & P. S. Meszaros (Eds.), *Reconfiguring the firewall: Recruiting women to information technology across cultures and continents* (pp. 147–160). AK Peters, Ltd.
- Cole, D., & Espinoza, A. (2011). The postbaccalaureate goals of college women in STEM. *New Directions for Institutional Research*, 152, 51-58.
- Cundiff, J. L., Vescio, T. K., Loken, E., & Lo, L. (2013). Do gender–science stereotypes predict science identification and science career aspirations among undergraduate science majors?. *Social Psychology of Education*, 16(4), 541-554.
- Cuny, J., & Aspray, W. (2002). Recruitment and retention of women graduate students in computer science and engineering: Results of a workshop organized by the Computing Research Association. *ACM SIGCSE Bulletin*, 34(2), 168-174.
- Eagan, M. K., Hurtado, S., Chang, M. J., Garcia, G. A., Herrera, F. A., & Garibay, J. C. (2013). Making a difference in science education: The impact of undergraduate research programs. *American Educational Research Journal*, 50(4), 683–713.
- English, D., & Umbach, P. D. (2016). Graduate school choice: An examination of individual and institutional effects. *The Review of Higher Education*, 39(2), 173-211.
- Flaherty, C. (2018, May 9). System crash. *Inside Higher Ed*.  
<https://www.insidehighered.com/news/2018/05/09/no-clear-solution-nationwide-shortage-computer-science-professors>
- Hambrusch, S., Libeskind-Hadas, R., & Aaron, E. (2015). Understanding the U.S. domestic computer science Ph.D. pipeline. *Communications of the ACM*, 58(5), 29-32.
- Herrera, F. A., Hurtado, S., & Chang, M. (2011, November 17-19). *Maintaining career aspirations in science, technology, engineering, and mathematics (STEM) among college students* [Paper presentation]. Association for the Study of Higher Education Annual Meeting, Charlotte, NC, United States.
- Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural equation modelling: Guidelines for determining model fit. *The Electronic Journal of Business Research Methods*, 6(1), 53-60.
- Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indices in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling*, 6(1), 1-55.

- Kapoor, A., & Gardner-McCune, C. (2018). Understanding professional identities and goals of computer science undergraduate students. In *Proceedings of the 49<sup>th</sup> ACM SIGCSE Technical Symposium on Computer Science Education (SIGCSE '18)*, 191-196.
- Kurose, J. (2017, July 3). *Dear colleague letter: Pursuing meaningful actions in support of broadening participation in computing (BPC)* (NSF Publication No. 17-110). National Science Foundation. <https://nsf.gov/pubs/2017/nsf17110/nsf17110.pdf>
- Kyoung Ro, H., Lattuca, L. R., & Alcott, B. (2017). Who goes to graduate school? Engineers' math proficiency, college experience, and self-assessment of skills. *Journal of Engineering Education*, 106(1), 98-122.
- Langin, K. (2019, May 29). A wave of graduate programs drops the GRE application requirement. *Science*. <https://www.sciencemag.org/careers/2019/05/wave-graduate-programs-drop-gre-application-requirement>
- Lehman, K. J., Wofford, A. M., Sendowski, M., Newhouse, K. N. S., & Sax, L. J. (2020). Better late than never: Exploring students' pathways to computing in later stages of college. In *Proceedings of the 51<sup>st</sup> ACM SIGCSE Technical Symposium on Computer Science Education (SIGCSE '20)*, 1075-1081. <https://doi.org/10.1145/3328778.3366814>
- Lent, R. W. (2016). Self-efficacy in a relational world: Social cognitive mechanisms of adaptation and development. *The Counseling Psychologist*, 44(4), 573-594.
- Lent, R. W., Brown, S. D., & Hackett, G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice, and performance. *Journal of Vocational Behavior*, 45(1), 79-122.
- Lent, R. W., Brown, S. D., & Hackett, G. (2000). Contextual supports and barriers to career choice: A social cognitive analysis. *Journal of Counseling Psychology*, 47(1), 36-49.
- Lent, R. W., Brown, S. D., & Hackett, G. (2002). Social cognitive career theory. In Duane Brown and Associates (Eds.), *Career choice and development* (4<sup>th</sup> ed., pp. 255-311). Jossey-Bass.
- Lent, R. W., Brown, S. D., & Larkin, K. C. (1986). Self-efficacy in the prediction of academic performance and perceived career options. *Journal of Counseling Psychology*, 33(3), 265-269.
- Lent, R. W., Lopez Jr, A. M., Lopez, F. G., & Sheu, H. B. (2008). Social cognitive career theory and the prediction of interests and choice goals in the computing disciplines. *Journal of Vocational Behavior*, 73(1), 52-62.
- Lent, R. W., Lopez, F. G., Sheu, H. B., & Lopez Jr, A. M. (2011). Social cognitive predictors of the interests and choices of computing majors: Applicability to underrepresented students. *Journal of Vocational Behavior*, 78(2), 184-192.

- Litzler, E., Samuelson, C. C., & Lorah, J. A. (2014). Breaking it down: Engineering student STEM confidence at the intersection of race/ethnicity and gender. *Research in Higher Education, 55*(8), 810-832.
- Malcom, L. E., & Dowd, A. C. (2012). The impact of undergraduate debt on the graduate school enrollment of STEM baccalaureates. *The Review of Higher Education, 35*(2), 265-305.
- Mandel, T., & Mache, J. (2017). Examining PhD student interest in teaching: An analysis of 19 years of historical data. In *Proceedings of the 48<sup>th</sup> ACM SIGCSE Technical Symposium on Computer Science Education (SIGCSE '17)*, 713.  
<https://doi.org/10.1145/3017680.3022427>
- Manly, C. A., & Wells, R. S. (2015). Reporting the use of multiple imputation for missing data in higher education research. *Research in Higher Education, 56*(4), 397-409.
- Margolis, J., & Fisher, A. (2002). *Unlocking the clubhouse: Women in computing*. MIT press.
- Merolla, D. M., & Serpe, R. T. (2013). STEM enrichment programs and graduate school matriculation: The role of science identity salience. *Social Psychology of Education, 16*(4), 575-597.
- Muthén, L. K., & Muthén, B. O. (1998-2017). *Mplus user's guide* (8<sup>th</sup> ed). Muthén & Muthén.
- National Academies of Sciences, Engineering, and Medicine. (2017). *Assessing and responding to the growth of computer science undergraduate enrollments*. The National Academies Press. <https://doi.org/10.17226/24926>
- National Academies of Sciences, Engineering, and Medicine. (2019). *The science of effective mentorship in STEMM*. The National Academies Press. <https://doi.org/10.17226/25568>
- Payton, J., & Souvenir, R. (2016). Broadening participation: Meeting the need for diverse faculty. *ACM SIGCSE Bulletin, 48*(1), 10.
- Perna, L. (2004). Understanding the decision to enroll in graduate school: Sex and racial/ethnic group differences. *The Journal of Higher Education, 75*(5), 487-527.
- Poon, O., Squire, D., Kodama, C., Byrd, A., Chan, J., Manzano, L., Furr, S., & Bishundat, D. (2016). A critical review of the model minority myth in selected literature on Asian Americans and Pacific Islanders in Higher Education. *Review of Educational Research, 86*(2), 469-502.
- Riegle-Crumb, C., Moore, C., & Ramos-Wada, A. (2011). Who wants to have a career in science or math? Exploring adolescents' future aspirations by gender and race/ethnicity. *Science Education, 95*(3), 458-476.

- Rocconi, L. M., Ribera, A. K., & Nelson Laird, T. F. (2015). College seniors' plans for graduate school: Do deep approaches learning and Holland academic environments matter? *Research in Higher Education, 56*, 178-201.
- Rodriguez, S. L., & Lehman, K. (2018). Developing the next generation of diverse computer scientists: The need for enhanced, intersectional computing identity theory. *Computer Science Education, 27*(3-4), 229-247.
- Rorrer, A. S., Allen, J., & Zuo, H. (2018). A national study of undergraduate research experiences in computing: Implications for culturally relevant pedagogy. In *Proceedings of the 49<sup>th</sup> ACM SIGCSE Technical Symposium in Computer Science Education (SIGCSE '18)*, 604-609.
- Rottinghaus, P. J., Lindley, L. D., Green, M. A., & Borgen, F. H. (2002). Educational aspirations: The contribution of personality, self-efficacy, and interests. *Journal of Vocational Behavior, 61*(1), 1-19.
- Sander, P., & Sanders, L. (2006). Understanding academic confidence. *Psychology Teaching Review, 12*(1), 29-42.
- Satorra, A., & Bentler, P. M. (1994). Corrections to test statistics and standard errors in covariance structure analysis. In A. von Eye & C. C. Clogg (Eds.), *Latent variables analysis: Applications for developmental research* (pp. 399-419). Sage.
- Sax, L. J. (2001). Undergraduate science majors: Gender differences in who goes to graduate school. *The Review of Higher Education, 24*(2), 153-172.
- Sax, L. J., George, K. L., Wofford, A.M., Sundar, S. (2019, November 14-16). *The tech trajectory: Examining the role of college environments in enhancing a diverse pipeline to computing careers* [Paper presentation]. Association for the Study of Higher Education Annual Meeting, Portland, OR, United States.
- Sax, L. J., Kanny, M. A., Riggers-Piehl, T. A., Whang, H., & Paulson, L. N. (2015). “But I’m not good at math”: The changing salience of mathematical self-concept in shaping women’s and men’s STEM aspirations. *Research in Higher Education, 56*(8), 813-842.
- Sax, L. J., & Newhouse, K. N. S. (2019). Disciplinary field specificity and variation in the STEM gender gap. *New Directions for Institutional Research, 179*, 45-71.  
<https://doi.org/10.1002/ir>
- Schafer, J. L., & Graham, J. W. (2002). Missing data: Our view of the state of the art. *Psychological Methods, 7*(2), 147-177. <https://doi.org/10.1037/1082-989x.7.2.147>
- Singer, N. (2019, January 24). The hard part of computer science? Getting into class. *The New York Times*. <https://www.nytimes.com/2019/01/24/technology/computer-science-courses-college.html>

- Strayhorn, T. L. (2010). Undergraduate research participation and STEM graduate degree aspirations among students of color. *New Directions for Institutional Research*, 2010(148), 85-93.
- Sullivan, P., Simmons, M., Moore, K., Meloncon, L., & Potts, L. (2015). Intentionally recursive: A participatory model for mentoring. In *Proceedings of the ACM SIGDOC International Conference on the Design of Communication*, 1-23.  
<https://doi.org/10.1145/2775441.2814672>
- Szelényi, K., & Inkelas, K. (2011). The role of living-learning programs in women's plans to attend graduate school in STEM fields. *Research in Higher Education*, 52(4), 349-369.
- Tamer, B., & Stout, J. G. (2016a). Understanding how research experiences for undergraduate students may foster diversity in the professorate. In *Proceedings of the 47<sup>th</sup> ACM SIGCSE Technical Symposium on Computer Science Education (SIGCSE '16)*, 114-119.
- Tamer, B., & Stout, J. G. (2016b). Recruitment and retention of undergraduate students in computing: Patterns by gender and race/ethnicity. <http://cra.org/cerp/research-findings/>
- Trytten, D. A., Lowe, A. W., & Walden, S. E. (2012). "Asians are good at math. What an awful stereotype": The model minority stereotype's impact on Asian American engineering students. *Journal of Engineering Education*, 101(3), 439-468.
- Ullman, J. B. (2006). Structural equation modeling: Reviewing the basics and moving forward. *Journal of Personality Assessment*, 87(1), 35-50.  
[https://doi.org/10.1207/s15327752jpa8701\\_03](https://doi.org/10.1207/s15327752jpa8701_03)
- Ullman, J. B., & Bentler, P. M. (2013). Structural equation modeling. In J. A. Schinka, W. F. Velicer, & I. B. Weiner (Eds.), *Handbook of psychology: Research methods in psychology* (pp. 661-690). John Wiley & Sons Inc.
- Wilson, B. C., & Shrock, S. (2001). Contributing to success in an introductory computer science course: A study of twelve factors. In *Proceedings of the 32<sup>nd</sup> ACM SIGCSE Technical Symposium on Computer Science Education (SIGCSE '01)*, 184-188.  
<https://doi.org/10.1145/364447.364581>
- Wofford, A. M. (2019). Enhancing support and self-confidence for graduate school admission: Early findings from the computing field. *NAGAP Perspectives*, 31(2), 23-27.
- Wolf, E. J., Harrington, K. M., Clark, S. L., & Miller, M. W. (2013). Sample size requirements for structural equation models: An evaluation of power, bias, and solution propriety. *Educational and Psychological Measurement*, 76(6), 913-934.  
<https://doi.org/10.1177/0013164413495237>
- Xu, Y. J. (2016). Aspirations and application for graduate education: Gender differences in low participation STEM disciplines. *Research in Higher Education*, 57(8), 913-942.

Zweben, S., & Bizot, B. (2018). *2017 CRA Taulbee survey: Another year of record undergrad enrollment; doctoral degree production steady while master's production rises again*. Computing Research Association. <https://cra.org/wp-content/uploads/2018/05/2017-Taulbee-Survey-Report.pdf>

**CHAPTER 3:**  
**INEQUITABLE INTERACTIONS? A CRITICAL QUANTITATIVE ANALYSIS OF**  
**MENTORSHIP AND PSYCHOSOCIAL DEVELOPMENT WITHIN COMPUTING**  
**GRADUATE SCHOOL PATHWAYS**

**Introduction**

Scientific graduate education in the United States holds a pivotal place in guiding key innovations and training future faculty. Despite the rapidly changing nature of knowledge in science, technology, engineering, mathematics, and medicine (STEMM), however, the diversification of pathways to graduate school programs has not kept pace. Indeed, the National Academies of Science, Engineering, and Medicine (2018) noted, “The pool of *potential* STEM graduate students is increasingly diverse, and research disciplines and institutions are striving—though many continue to struggle—to be more inclusive and equitable, in terms of both representation and institutional climate” (p. 29). The emphasis of “potential” in the preceding quote signals a sizable opportunity to foster students’ interest in STEMM graduate programs, especially the graduate school interests of students who have been historically minoritized (e.g., due to their gender, class, racial/ethnic identities). Yet, there are also important differences across STEMM disciplines, and exploring such distinctions may provide insight as to how disparities vary across STEMM fields (Cheryan et al., 2017; Sax & Newhouse, 2019) as well as how to cater equity-driven suggestions to particular disciplinary contexts.

Within STEMM, computing represents a unique case. Computing disciplines currently show exponential growth in professional opportunities (Bureau of Labor Statistics [BLS], 2019) while remaining one of the least diverse STEMM fields (National Center for Science and Engineering Statistics [NCSES], 2019). Computing departments face many challenges in

fostering equitable environments and outcomes for historically minoritized students, especially in the face of recent enrollment gains (Computing Research Association [CRA], 2017). These challenges within computing are exacerbated by a faculty shortage, a lack of faculty diversity, and difficulties filling faculty positions due to the workforce marketability of computing skills (CRA, 2017; Singer, 2019). One way to learn more about the barriers and opportunities to building inclusive pathways in computing, particularly pathways toward the professoriate, is to focus on students' early experiences in graduate school trajectories—such as the time between computing undergraduates' displayed interest in graduate degrees and the time at which they make concrete future plans. Graduate degrees are often a prerequisite for computing faculty positions (Mandel & Mache, 2017), and I posit that examining the (in)equitable support that individuals in computing departments provide to graduate school aspirants may help institutional actors understand what tips the scales of decision-making in students' post-baccalaureate plans.

Researchers have argued that mentoring relationships may be one way to foster equity-driven changes to institutional culture, individual support, and students' graduate school plans in science (NASEM, 2019; Packard, 2016). Students' mentoring experiences in computing shape how they develop a variety of skills, beliefs, and goals. Specifically, disciplinary psychosocial beliefs (e.g., computing self-efficacy, computing identity) are key to students' development and may mediate later educational and vocational decisions in computing. Often, undergraduate students' perceptions of who can become a computer scientist or pursue computing in graduate school are molded by role models in college (Charleston et al., 2014; Cheryan et al., 2013).

Despite the possible benefits, mentoring relationships and their outcomes in computing are not well understood. While scholars have found that short-term mentoring interventions foster students' growth in computing (Boyer et al., 2010; Pon-Barry et al., 2017), few have

examined computing students' broader mentorship experiences, especially with regard to who serves as a mentor (e.g., faculty, staff, peers) and how mentoring relationships shape graduate school plans. Exploring how mentorship fosters or hinders the disciplinary development of computing students with graduate school aspirations is a crucial focus, as students with stronger computing self-efficacy and identity may be more likely to act upon their aspirations through graduate school enrollment. Using a sample of undergraduate students who had a mentor in their computing department and held graduate school aspirations, this study examines the nature of departmental mentorship, how mentorship is associated with graduate aspirants' psychosocial development, and the conditional effects of mentoring support. The following questions guide this inquiry:

1. Among graduate school aspirants, whom do undergraduate students identify as their primary mentors in computing departments?
2. Among graduate school aspirants, how does the nature of mentoring support that students receive in computing departments vary by the mentor's role as well as students' identities?
3. Among graduate school aspirants, what aspects of mentoring relationships in computing departments predict students' computing self-efficacy and computing identity? How does the salience of mentoring support vary by the mentor's role and students' identities?

### **Context on Mentorship Across Disciplines**

Mentoring has been widely documented as a vital influence on undergraduate students' development (see Crisp et al., 2017; Jacobi, 1991) as well as students' longer-term trajectories, such as their plans for graduate school (e.g., Luna & Prieto, 2009; Trolan & Parker, 2017) or sense of life purpose (Lund et al., 2019). Further, mentorship may provide crucial support to

students who have been historically minoritized in college due to their social identities, such as gender, race/ethnicity, sexuality, or class (e.g., Dugan et al., 2012; McCoy et al., 2020). Mentors can help historically minoritized students navigate challenging campus environments where they might feel oppressed (Benishek et al., 2004) and may hold the power to change these larger oppressive environments (Ragins, 1995). Yet, scholars have also shown that mentorship may reinforce institutional inequities, particularly when considered alongside the gendered and racialized histories of academic disciplines (Davis et al., 2015). To promote positive outcomes, it is critical to understand the nature of mentorship. It is especially important to understand how mentorship operates in collegiate contexts like computing, as effective mentoring may provide one way for computing departments to bolster equitable outcomes among undergraduates as they prepare for future educational and vocational opportunities.

### **Mentorship in STEMM and Computing Disciplines**

Extant research has examined undergraduate mentoring in STEMM by addressing how mentorship affects career or psychosocial outcomes (e.g., Anderson et al., 2019; Byars-Winston et al., 2015). While mentorship is often related to positive growth for STEMM undergraduates, challenges—such as mentor availability or communication—may lead to negative outcomes (Limeri et al., 2019; Sullivan et al., 2015). While research on STEMM mentorship has grown (see NASEM, 2019), there remains a lack of clarity about how mentoring practices vary within STEMM. Disaggregating STEMM fields is vital, as disciplinary cultures (including mentoring environments and the mentors/mentees who participate) are starkly different. Without attending to disciplinary differences, institutions may be limited in how they can address the resultant inequities from mentorship in ways that align with the divergent needs of particular fields.

Computing is uniquely situated in STEMM, as a faculty shortage has reduced the time and resources faculty have to serve as mentors (CRA, 2017). In addition, when departments have attended to mentoring structures, many have focused on bounded efforts like undergraduate research experiences (UREs), introductory courses, or professional organizations (Hug & Jurow, 2013; Pon-Barry et al., 2017; Rorrer et al., 2018). As such, there remains a need to address how students' mentorship in computing departments relates to their post-baccalaureate plans. To date, few studies have examined mentorship in students' computing graduate pathways (Cohoon & Lord, 2007; Wofford, 2021; Wofford et al., forthcoming). As computing departments strive to grow and diversify graduate enrollments, this is a vital gap to address. To provide context, I first discuss what is known about mentorship in computing. I then address how mentorship in computing shapes psychosocial beliefs, focusing on the importance of equity in such development.

## **Literature Review**

### **Mentorship in Computing Departments**

Computing departments have—to varying extents—implemented structured mentoring experiences in the curriculum, and scholars have documented how faculty and undergraduate peers are key mentors in these environments (Charleston et al., 2014; Cohoon et al., 2004; Ogan & Robinson, 2008; Pon-Barry et al., 2017). For one, some departments have targeted mentorship efforts for introductory courses (Miller & Kay, 2002; Pon-Barry et al., 2017; Tashakkori et al., 2005). Introductory courses are critical gateways in computing, and studies have shown how early relationships with multiple mentors (e.g., faculty, graduate students, undergraduate peers) may impact students' introductory course success and their long-term commitment to computing (Pon-Barry et al., 2017; Tashakkori et al., 2005).

If introductory course students engage in positive mentoring relationships and gain confidence in their computing skills (Fryling et al., 2018; Pon-Barry et al., 2017), they may also be more likely to pursue future departmental opportunities, such as computing UREs or affinity groups. Because UREs involve faculty-led projects, they provide a natural setting for mentorship (Rorrer et al., 2018; Tamer & Stout, 2016). Further, departmental programs such as Women in Academic Computing (Hug & Jurow, 2013) or Computing Identity Mentoring (Boyer et al., 2010) may be important environments for mentors to provide guidance aligned with mentees' social identities. However, offering access to mentorship is not enough to ensure that mentorship has a positive effect on students' development.

It is also essential to acknowledge that gender and racial identity concordance in STEMM mentoring relationships has been a focus of recent research (Blake-Beard et al., 2011; Hodari et al., 2014; Newman, 2015). Yet, findings have been inconclusive about the importance of identity concordance in STEMM mentorship. While some researchers have supported the community-building potential of identity concordance (Hodari et al., 2014), others have argued that mentoring relationships with deep-level similarities (e.g., shared beliefs, trust) may be more effective than relationships with similarities across visible identities alone (NASEM, 2019; Newman, 2015). That is to say, in order to foster effective mentorship, it is necessary to learn more about students' perceptions of their mentors' values and beliefs—many of which may be evident in the types of support mentors provide.

### **Mentorship and Computing Graduate School Pathways**

While some researchers have found that mentorship supports students' plans for graduate school across disciplines (e.g., Luna & Prieto, 2009; Trolan & Parker, 2017), only a small body of literature has focused on the relationship between mentorship and graduate school plans in

computing. Among these studies, scholars have documented the positive association that faculty support has with sustaining introductory computing students' initial graduate aspirations (Wofford et al., forthcoming) and discussed the benefits of faculty and peer mentorship on undergraduates' progression to graduate school matriculation (Charleston, 2012; Cohoon et al., 2004). Yet, less is known about the space between graduate aspiration and matriculation in computing, and mentors may be crucial in helping computing students navigate graduate school applications and decisions about enrollment. While Wofford (2021) illustrated that mentoring support during introductory computing courses, when combined with the development of computing self-efficacy, may contribute to students' confidence for graduate school admission, it is important to further explore the qualities of mentoring support that might shape these developmental pathways and investigate whether mentoring support is equitably provided to graduate aspirants.

### **Psychosocial Outcomes of Undergraduate Mentorship in Computing**

Science self-efficacy and identity are arguably two of the most important psychosocial outcomes of STEMM mentorship (e.g., Byars-Winston et al., 2015; Cole & Espinoza, 2011). While science self-efficacy is more concerned with individuals' confidence in mastering specific tasks and science identity often embodies individuals' overall perceptions of self as a "science person," undergraduate students frequently develop both affective beliefs concurrently (Williams & George-Jackson, 2014). Mentors are often crucial in shaping these psychosocial beliefs; yet, depending on the quality of mentorship, students' developmental trajectories may not be uniformly positive and may fluctuate over time (NASEM, 2019). Given the scope of this study, I situate the present work in conversation with research on computing identity and self-efficacy—

both of which have been illustrated as vital to students' participation in STEMM graduate school and careers (Byars-Winston & Rogers, 2019; Chemers et al., 2011).

### ***Computing Identity***

Extant research has suggested that mentors are critical to undergraduate students' science identity development (Aikens et al., 2017; Chemers et al., 2011; Hurtado et al., 2009; Robnett et al., 2018). Yet, scholars have only recently investigated the unique traits of *computing* identity (Taheri et al., 2018, 2019). Computing identity, or the ways one feels like a “computing person,” underscores students' commitment to computing (Kapoor & Gardner-McCune, 2018; Taheri et al., 2019). For example, Taheri and colleagues (2019) found that computing identity is associated with higher levels of persistence in undergraduate computing. However, less is known about how computing identity develops, particularly when it comes to the role of various mentors in this process. Further, to advance equitable outcomes of mentorship, computing identities must be considered in the context of students' social identities (Rodriguez & Lehman, 2018). Without doing so, mentors may lead historically minoritized students to compartmentalize aspects of their social identities when they feel that these identities conflict with being a computing person.

### ***Computing Self-Efficacy***

In addition to shaping disciplinary identity, mentors also influence undergraduate students' science self-efficacy (Aikens et al., 2016; Byars-Winston et al., 2015). Recently, scholars have shown increasing interest in operationalizing disciplinary-specific self-efficacy measures—in this case, computing self-efficacy (Kolar et al., 2013). Computing self-efficacy measures students' confidence in successfully executing particular technical skills and has been found to significantly predict undergraduate students' computing career interests (Sax et al., 2019) and graduate school plans (Wofford, 2021; Wofford et al., forthcoming). Research has

also documented the direct and indirect ways that mentorship support shapes computing self-efficacy (Blaney & Stout, 2017; Wofford, 2021). While it is useful to know that mentors can guide students' computing self-efficacy development, much remains to be learned about the nuances of who provides such mentorship, the types of mentoring behaviors that shape computing self-efficacy, and whether such mentorship differentially affects historically minoritized students.

### **Addressing the Empirical and Epistemological Gap**

While scholars have noted the importance of computing identity, computing self-efficacy, and suggested that mentorship fosters these psychosocial beliefs, prior studies have not detailed specific forms of mentoring support in computing (Goh et al., 2007; Hodari et al., 2014). This lack of clarity about mentoring support, coupled with the urgent need for greater equity in computing, creates a compelling case to investigate the nature and outcomes of mentorship in computing departments. Further, Wofford and colleagues (forthcoming) documented that computing self-efficacy and identity positively predict students' computing graduate aspirations. Thus, knowing how psychosocial beliefs develop *among* graduate aspirants may reveal new insights about how to support the translation of graduate aspirations into application and matriculation decisions.

Of note, I extend prior research by taking a critical quantitative approach in research motivation, design, and interpretation (Stage, 2007; Stage & Wells, 2014). Critical quantitative work is often motivated by social transformation and analytically attends to the perspectives of historically minoritized students (Stage, 2007). I embrace these epistemological foundations by investigating how mentorship may be an important lever to cultivate more equitable experiences

and outcomes in collegiate computing departments, while interpreting mentoring experiences in the context of organizational and societal power dynamics.

In adopting a critical quantitative lens, I devised questions that center on inequities related to students' identities and the roles of mentors in computing departments. I also grappled with my biases and positionality throughout analyses, and my methodological decisions (e.g., retaining small sample sizes, using weighted effect coding instead of traditional reference groups) were guided by the imperatives of critical quantitative work. Further, by conceptually applying a power perspective, I interpret these results with an eye toward the (in)equitable nature of mentoring support that graduate aspirants in computing departments receive and how policy and advocacy efforts may take steps toward resolving some of these disparities.

### **Conceptual Framework**

The primary framework for this study is Crisp and colleagues' (2017) framework of mentoring undergraduate students. This framework outlines integral connections between students' identities and backgrounds, educational contexts (e.g., departmental and mentor characteristics), mentoring relationship features (e.g., mentorship purpose, duration), forms of mentoring support, and resultant student outcomes. Given my focus on graduate school aspirants' psychosocial development in computing, I adapted this framework to situate mentoring relationships in a computing-specific context (discussed further in the methods).

At the foundation of this model, Crisp et al. (2017) posited that students' characteristics and their educational contexts serve to inform one another. In other words, students' social identities and prior experiences inform the ways in which they participate in their college environment, while the university context also plays a role in shaping students' identities. Together, these individual and organizational characteristics impact the breadth (i.e., intent,

purpose, intensity) and depth (i.e., length) of mentoring relationships and how students navigate access to and engagement in mentorship. In addition, Crisp and colleagues outlined a relationship between background traits, educational characteristics, and the specific types of practices that mentors engage in—referred to as “forms of support,” which are of central importance to this model and the present study.

Drawing from earlier research (see Crisp, 2009), Crisp et al. (2017) articulated four categories of mentoring support: psychological and emotional (e.g., encouraging behaviors), degree completion (e.g., advising students through policies and requirements), academic subject knowledge (e.g., doing research with students, sharing disciplinary resources), and career development (e.g., role modeling). Crisp and colleagues discussed how students may receive multiple forms of mentoring support, with the nature of support guided by the educational context, the role and power of the mentor, and students’ identities. As a result, these dimensions are posited to impact both intermediate outcomes (e.g., psychosocial development, social capital) and longer-term outcomes (e.g., academic success, educational trajectories).

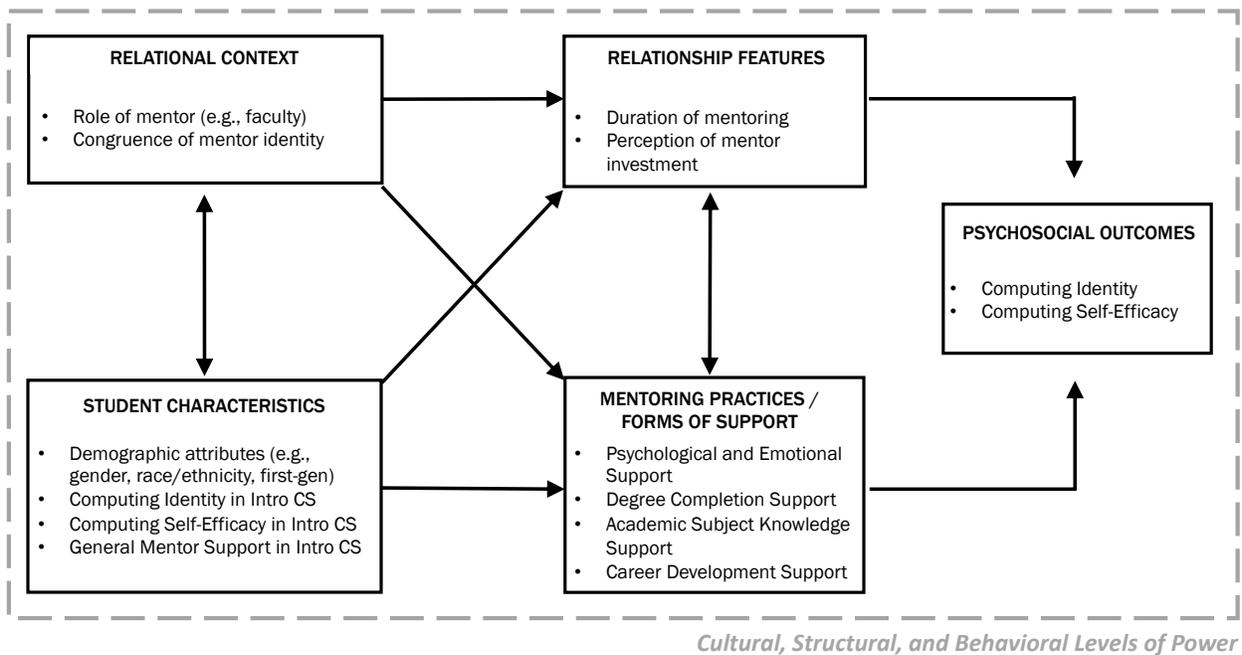
While Crisp et al.’s (2017) model grounds the variable selection and scope of this study, I extend this framework by incorporating a power perspective (Ragins, 1995, 1997). Specifically, I apply Ragins’s (1995) theoretical framework of organizational change, which draws from literature on diversity, power, and mentorship at cultural, structural, and behavioral levels. In this framework, Ragins discussed how the cultural level speaks to the foundational beliefs that an organization holds of itself, the structural level considers the organizational grouping of positions, and the behavioral level focuses on individual perceptions. While the data source for this study allows me to most closely address the behavioral level of mentorship (via exploring

the support that graduate aspirants receive), I leverage the structural and cultural levels to discuss larger structures of positional power and disciplinary culture in computing departments.

Collectively, I take a disciplinary-specific approach to examine mentorship in computing departments among undergraduates who aspire to graduate school. Given that disciplinary knowledge underscores graduate school preparation (Flaster et al., 2020), I focus on how departmental mentoring relationships (in)equitably shape students' development of computing self-efficacy and computing identity (see Figure 1).

**Figure 1**

*Framework for Power and Mentorship in Computing Departments, Adapted from Crisp et al. (2017) and Ragins (1995)*



## Methods

### Data Source

This study relied on data from the BRAID (Building, Recruiting, and Inclusion for Diversity) Research project, a longitudinal, mixed-methods study of efforts to diversify undergraduate computing. Computing departments at each BRAID institution (13 public and two private doctoral-granting universities) made specific commitments related to recruiting and retaining historically minoritized students in computing (see AnitaB.org, n.d.). To learn more about the outcomes of this initiative, the BRAID Research team has followed two cohorts of undergraduate students, all of whom took an introductory computing course in 2015-2016 (Cohort A) or 2016-2017 (Cohort B). Initial data collection involved surveying students at the beginning and end of their introductory course. For each intro course survey, the first 400 respondents (across all institutions) received a \$15 Amazon gift card, and all respondents were entered into a raffle for one of two \$125 Amazon gift cards. If a student responded to at least one introductory course survey, they received annual invitations to participate in follow-up surveys.

Follow-up data collection is ongoing, and the research team has continued to invite introductory course survey respondents to complete annual surveys (from 2016 to 2020). Follow-up surveys have evolved to examine students' retrospective views of undergraduate computing and post-college plans. In contrast to the incentive structure used for introductory course surveys, all follow-up survey respondents were guaranteed a \$10 or \$20 Amazon gift card<sup>5</sup>. Details about survey response rates are provided in the Appendix, Table A1.

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<sup>5</sup> Follow-up surveys from 2016-2018 used a \$10 Amazon gift card as an incentive, while the 2019 and 2020 follow-up surveys used an increased incentive of a \$20 Amazon gift card.

## **Study Sample**

Data for this study were drawn from a longitudinal sample of undergraduate students who completed a survey at the end of their introductory course in 2015-2016 (Cohort A) or 2016-2017 (Cohort B) and a follow-up survey in fall 2019 ( $n = 1,884$ ). These specific time points are important, as survey items addressing mentoring experiences were newly added in fall 2019.

Given the focus on mentorship in computing departments, I restricted the sample to reflect this scope. First, the sample was filtered to include students who identified having a mentor in their major or department ( $n = 1,268$ ). Additionally, I restricted the sample to computing majors on the follow-up survey to match this focus ( $n = 644$ ). Finally, to more deeply explore departmental mentorship among students who aspire to graduate school, I limited the sample to those who reported aspirations for a master's or doctoral degree on either survey ( $n = 442$ ). See Table A2 in the Appendix for a profile of respondents included in analyses.

## **Measures**

### ***Dependent Variables***

Two dependent variables served as psychosocial outcomes for this study. First, I created a latent construct of Computing Identity, which represents the extent to which individuals see themselves as “computing people.” Second, I tested and created a latent construct of Computing Self-Efficacy, representing students’ domain-specific confidence in mastering certain computing skills. Both factors were drawn from prior analyses (see Wofford, 2021) and tested using confirmatory factor analysis (CFA) with Promax rotation in SPSS (see Appendix, Table A4).

### ***Independent Variables***

This study focuses on understanding graduate aspirants’ mentoring relationships in computing departments and how features of such mentorship relate to graduate aspirants’

disciplinary psychosocial development. In light of this, I selected independent variables in alignment with Crisp and colleagues' (2017) framework.

**Student Characteristics.** In the first block, I included direct pre-tests for each dependent variable which accounted for students' initial psychosocial beliefs during introductory computing courses. I then created a factor illuminating students' perceptions of general mentoring support during intro courses. Notably, the Early General Mentoring Support factor captures students' broad perceptions of mentorship and could include support from faculty, peers, employers, family or community members, or others that students perceived to be in a mentoring role.

Second, I included variables measuring students' identities. Given that identity formation is ongoing, I used items from the follow-up survey to address the most current ways students described their gender, race/ethnicity, and sexuality (other identities were only observed on the first survey). In coding identity groups as well as other categorical variables, I used weighted effect coding as a way to analyze categorical groups and place results of subgroups relative to the weighted average of the group means (Daly et al., 2016), rather than using dummy coding, which often (un)intentionally privileges dominant students' narratives (e.g., white students, men). With weighted effect coding, "the midpoint or reference shifts away from the unweighted grand mean to the weighted sample mean" (te Grotenhuis et al., 2017, p. 165). Thus, categorical subgroup results are interpreted relative to the weighted sample mean—a mythical student average that avoids comparing students to each other while statistically accounting for the size of subgroups.

**Relational Context.** In the third block, I used several follow-up variables to investigate the relational context of students' mentorship experiences. While departmental context is illustrated in the scope of the sample (i.e., limiting the sample to computing majors), it is vital to consider the structural and interpersonal nature of students' relationships with their primary

mentor. As such, I controlled for the departmental role of the mentor as well as the racial/ethnic or gender identity congruence between mentors and mentees. Students could select their primary mentor from a variety of roles, such as undergraduate faculty advisor, academic advising staff, or advanced undergraduate peer.

**Relationship Features.** Based on the conceptual framework, I included two single-item variables in the fourth block that measured the breadth and depth of graduate aspirants' mentoring relationships with a primary mentor in the computing department. As such, I used variables assessing the duration of the mentoring relationship and the extent to which students perceived their mentor to be invested in a developmental relationship.

**Forms of Mentoring Support.** Finally, I accounted for the behaviors in which graduate aspirants reported their mentor to be engaged. I first tested four factors (i.e., Psychological and Emotional Support, Degree Completion Support, Academic Subject Knowledge Support, Career Development Support) using items adapted from the College Student Mentoring Scale (see Crisp, 2009). Across these items, students identified the extent to which their primary mentor in the computing department regularly enacted certain behaviors (see Appendix, Table A3) on a scale from 1 (*strongly disagree*) to 5 (*strongly agree*). While factors were statistically reliable, constructs concerning academic subject knowledge and career development were highly correlated ( $> .70$ ). I suspected that this high correlation may be partially due to the applied nature of the computing field, as the support needed to learn academic elements of computing may be similar to that which prepares you for a computing career. Given these concerns, I tested and used three revised factors for mentoring support: 1) Psychological and Emotional Support, 2) Degree Completion Support, and 3) Computing Field and Career Development Support.

## **Analyses**

### ***Descriptive Analyses***

To address the first research question, which descriptively concerns whom graduate aspirants in computing departments identified as their primary mentors, I relied on frequencies to investigate the distribution of mentorship across seven roles in the department. The second research question descriptively examines the nature of mentoring support in computing departments and how support varies by the mentor's role as well as students' social identities. To address this question, I used a series of one-way ANOVAs with Tukey post-hoc tests. Of methodological importance, ANOVAs relied on mean differences in factor scores, which are sensitive to the ways in which latent constructs are extracted and rotated in factor analysis (DiStefano et al., 2009), and these results should be interpreted as exploratory in nature.

### ***Inferential Analyses***

The final research question first concerns the aspects of departmental mentorship that shape graduate aspirants' computing self-efficacy and computing identity, and I examined this question by employing two ordinary least squares (OLS) regression models. Before running these analyses, I examined frequencies and missing data (see Table A4 in the Appendix) and, given the low amount of missing data, decided to preserve only students' true responses and not impute for missing data points. I then ran each regression model separately, controlling for identical main effects. By accounting for the same control variables (in five blocks, as described above), I explored how the predictive power of each independent variable diverged across models. The last part of the third research question prompted my use of interaction terms, as I was interested in addressing how the salience of the three mentoring support constructs

inferentially varied by the mentor's role as well as students' social identities (i.e., mentoring support\*mentor's role; mentoring support\*gender; mentoring support\*race/ethnicity).

### **Positionality**

In critical quantitative approaches, as with all research, positionality is vital to consider (Rios-Aguilar, 2014). I came to this work having many positive mentoring experiences; yet, I have also experienced tensions between well-meaning mentors and their gendered assumptions about my educational trajectory. My research motivation also draws from my experiences fostering mentorship opportunities for prospective STEMM graduate students while working in graduate school admissions. Throughout this work, I also grappled with how my social positions and privileges influenced my methodological choices and interpretations, particularly in a field where I remain an outsider. For example, in analyses, I considered whether I could use each disaggregated subgroup of students' identities as a way to center the perspectives of historically minoritized students. I deliberated many options and implications of varying levels of aggregation, depending on the data source and statistical tests, and reflected upon how my perceptions of limitations and opportunities in coding (and in other elements of this research) may be influenced by my positionalities—in known and unknown ways.

### **Limitations**

This study has a few key limitations. First, while the BRAID Research data are multi-institutional, data were collected at doctoral granting research universities, leaving much to be learned about how mentorship in computing varies by institutional context. Second, survey data collected limited details about students' racial and ethnic identities, which constrained my ability to contextualize the experiences of racially and ethnically minoritized students (e.g., survey did not capture whether Black students identified as having a family history of being enslaved in the

United States, as Black Caribbean, etc.). Survey structure also limited my ability to disaggregate other student traits, such as dis/ability<sup>6</sup>, in interpretable ways. Finally, it is also essential to acknowledge that quantitative analyses of student-level data—even when interpreted with structures of power in mind—do not paint the whole picture when it comes to mentorship, and future studies employing qualitative or mixed methods may robustly expand the knowledge base about mentoring relationships and graduate school trajectories in computing.

## Results

### Research Question One: Roles of Mentors in Computing Departments

Addressing the first research question, Table 1 illustrates the distribution of mentors' roles among graduate aspirants who had a primary mentor in the computing department. While there was wide variation, half (50.2%) of graduate aspirants revealed their primary mentors to be faculty members. Advanced undergraduate peers represented the next most common mentor, with 17.0% of graduate aspirants chiefly holding mentoring relationships with more senior-level peers in computing. About one-third of graduate aspirants selected one of the remaining options as their primary mentor (i.e., supervisors or professional colleagues, academic advising staff, graduate students, someone else). Among these remaining options, 12.9% of graduate aspirants indicated that individual to be a supervisor or professional colleague within their computing department, perhaps speaking to the professional and applied nature of the computing field.

### Research Question Two: Inequities in the Nature of Mentoring Support

The second research question concerns inequities in graduate aspirants' mentoring interactions. Exploratory one-way ANOVA results revealed several ways in which the nature of

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<sup>6</sup> In alignment with the work of Annamma and Handy (2021), I use *dis/ability* to “refuse the deficit notions situated in historical conceptions of disability, link how disability and ability rely on one another, and recognize the contested and unstable nature of both” (p. 47).

mentoring support diverged depending on the professional role mentors held. Table 2 illustrates significant differences in mean factor scores across all three constructs of mentoring support (i.e., Psychological and Emotional Support, Degree Completion Support, Computing Field and Career Development Support). These results suggest that the most salient differences are present in psychological and emotional support ( $F(6, 428) = 7.939; p < .001$ ). Graduate aspirants primarily mentored by advanced undergraduate peers, graduate students, or someone else reported notably higher mean factor scores on psychological and emotional support relative to graduate aspirants whose primary mentors were their faculty advisor or another computing faculty member. To investigate whether this result was due to the self-selective nature of the current sample (i.e., graduate school-aspiring computing majors with departmental mentors), I repeated this one-way ANOVA test among computing majors with departmental mentors who did *not* aspire to graduate school; these results confirmed the finding above that students primarily mentored by advanced undergraduate peers, graduate students, or someone else in the department indicated higher mean factor scores on psychological and emotional support than their peers mentored by any faculty member in the computing department.

Key differences also emerged with regard to degree completion support ( $F(6, 430) = 3.784; p = .001$ ), as shown in Table 2. Post-hoc tests illustrated that graduate aspirants whose departmental mentor was someone else reported significantly higher mean factor scores on degree completion support than students mentored by an advanced undergraduate peer. Further, Table 2 shows that graduate aspirants with another faculty mentor (non-advisor) reported significantly greater degree completion support than those with an advanced undergraduate peer mentor. Although there were no statistically significant differences across computing field and career development support, the highest levels of field-specific mentoring support appear to be

among graduate aspirants whose primary mentors were current graduate students, suggesting that undergraduates who aspire to earn a graduate degree may look to current graduate students for advice regarding this trajectory.

The latter part of the second research question prompted an examination of inequities across students' social identities. I first used one-way ANOVAs to test differences across all mentoring support constructs by discrete social identities (i.e., gender, race/ethnicity, transgender identity, first-generation status, social class, sexuality, and dis/ability), and statistically significant differences only emerged with regard to gender identity. Specifically, one-way ANOVA results ( $F(2, 432) = 3.944; p = .020$ ) revealed gender differences in receiving psychological and emotional mentoring support, with Tukey post-hoc tests illustrating that women indicated more psychological and emotional support than men ( $p = .040$ ). In light of these differences, I ran an additional one-way ANOVA to examine which individual items contributed to the statistical gender differences in the nature of psychological and emotional mentoring support (Table 3).

Table 3 shows statistically significant gender differences regarding the extent to which graduate aspirants felt their primary mentor provided emotional support, with women receiving more emotional support than men ( $F(2, 435) = 8.788; p < .0001$ ). Importantly, non-binary graduate aspirants may perceive their departmental mentors to provide a greater amount of emotional support as well, given the higher means, but it is likely that significance was not detected due to the small sample of non-binary students ( $n = 5$ ). No significant gender differences were detected across other items in the psychological and emotional mentoring support construct; however, it is noteworthy that women and non-binary graduate aspirants reported higher means on all items in this factor.

Next, given the disparities by gender, I examined potential inequities in psychological and emotional support across intersecting gender and racial/ethnic identities. While many other social identities are intertwined with gender, I focused on race/ethnicity because prior research has widely examined gender and racial/ethnic identity concordance in mentorship (as noted in the literature review). I first tried using one-way ANOVA with 14 disaggregated categories of intersecting identities. While significant results emerged across two items (i.e., emotional support, encouragement to talk about social life), post-hoc tests could not attribute differences to particular groups, likely due to small sample sizes and the number of groups. I then used a revised, aggregated approach<sup>7</sup> to explore inequities across six broader intersecting groups.

As illustrated in Table 4, one-way ANOVA results revealed significant differences ( $F(5, 423) = 4.004; p = .001$ ) across intersecting gender and racial/ethnic groups for only one of the four behaviors associated with the nature of psychological and emotional mentoring support: that of mentors providing emotional support. Using Tukey post-hoc tests, it became evident that graduate aspirants who identified as underrepresented Women of Color in computing (i.e., Black, Latina/x, Native, Arab, Persian, or Middle Eastern, and multiracially minoritized women) reported higher mean scores on emotional support than graduate aspirants who were white men or underrepresented Men of Color in computing.

### **Research Question Three: Examining How Departmental Mentorship Predicts**

#### **Psychosocial Beliefs**

To analyze the extent to which varying features of departmental mentoring relationships predict disciplinary psychosocial development among graduate aspirants with primary mentors in

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<sup>7</sup> Included six groups for men and women across racial/ethnic identities of white, Asian or Asian American (including multiracial Asian and white), and underrepresented Students of Color in computing (USOCC). ANOVAs could not employ statistical tests with non-binary subgroups, due to  $n < 2$  in more than one racial/ethnic group.

computing departments, I ran two OLS regression models predicting computing self-efficacy and computing identity, which, sans the pre-test, were identical models (e.g., introductory course computing identity was the only pre-test entered in the computing identity regression).

### ***Main Effects***

Results from both final regression models (i.e., models controlling for all main effects) are presented as Model 1 in Tables 5 and 6. I discuss these models collectively, as I aimed to compare the features of mentorship associated with students' computing self-efficacy with those predicting computing identity. Overall, independent variables concerning graduate aspirants' departmental mentoring relationships were better predictors of computing identity ( $R^2 = 30.2\%$ ) than computing self-efficacy ( $R^2 = 24.0\%$ ). Much of this predictive power can be attributed to students' earlier psychosocial beliefs during the introductory course (Block 1), as indicated by the salience of computing self-efficacy ( $\beta = 0.38$ ;  $p < .001$ ) and computing identity ( $\beta = 0.44$ ;  $p < .001$ ) factors as direct pre-tests on their respective outcomes. After controlling for Block 5, which included specific forms of mentoring support on the follow-up survey, results also show that, among graduate aspirants with departmental mentors in computing, broader mentoring support during introductory courses negatively predicted students' computing self-efficacy ( $\beta = -0.12$ ;  $p = .02$ ), while early general mentorship did not play a similar role for computing identity.

Next, Block 2 revealed several differences in how graduate aspirants' identities relate to disciplinary psychosocial development, net of controlled mentoring variables. First, multiracial graduate aspirants who identified as Asian, Asian American, and/or white had higher levels of computing self-efficacy ( $\beta = 0.10$ ;  $p = .04$ ), relative to the weighted sample mean of students' racial/ethnic identities. No salient racial/ethnic differences emerged with regard to computing

identity; however, results indicated differences in computing identity for men and women<sup>8</sup>.

Relative to the weighted sample mean of students' gender identities, men reported higher levels of computing identity ( $\beta = 0.18$ ;  $p < .001$ ), while women graduate aspirants reported lower levels of computing identity ( $\beta = -0.19$ ;  $p < .001$ ). No other significant differences were detected.

Block 3 (mentoring relational context) in Table 5 shows that mentors who were other professors (non-advisors) and those who were undergraduate faculty advisors shaped computing self-efficacy, though in opposite ways. Compared to the weighted sample mean of primary mentors' departmental roles, graduate aspirants with other faculty mentors had higher levels of computing self-efficacy ( $\beta = 0.15$ ;  $p = .01$ ), whereas having an undergraduate faculty advisor as a primary mentor was negatively associated with computing self-efficacy ( $\beta = -0.11$ ;  $p = .05$ ). Notably, block-by-block changes in the computing identity model (Table 6) revealed that the role of other faculty mentors (non-advisors) was significant until mentoring support variables entered. This suggests that the behaviors mentors engage in may be more strongly associated with computing identity than what role mentors occupy.

Variables controlling for the breadth and depth of departmental mentorship were entered in Block 4. While Table 5 shows no statistically significant differences in computing self-efficacy, Table 6 illustrates that graduate aspirants who felt their primary mentor was more invested in their relationship also reported significantly higher levels of computing identity ( $\beta = 0.13$ ;  $p = .02$ ). In some ways, graduate aspirants' perceptions of investment may naturally relate more to their disciplinary identity development, given the deeply intrinsic nature of both facets.

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<sup>8</sup> In this sample, "women" includes two self-identified trans women, while "men" solely includes cisgender men.

Finally, forms of departmental mentoring support in computing entered in Block 5 (see Tables 5 and 6). Among these factors, both regressions solely illustrated degree completion support as significant. Degree completion support was strongly associated with fostering computing self-efficacy, emerging as the second most salient variable ( $\beta = 0.27$ ;  $p < .001$ ). With computing identity, degree completion support played a significant and positive role but to a lesser strength ( $\beta = 0.13$ ;  $p = .04$ ). Despite other forms of mentoring support emerging as important (albeit sometimes inequitable) descriptively, regression results illuminated that the variance in these other forms of mentoring support was explained by other control variables. Given that this sample reflects graduate school aspirants and that degree completion support included items closely related to examining current and future educational options and the implications of such, the salience of this type of mentoring support is not entirely surprising.

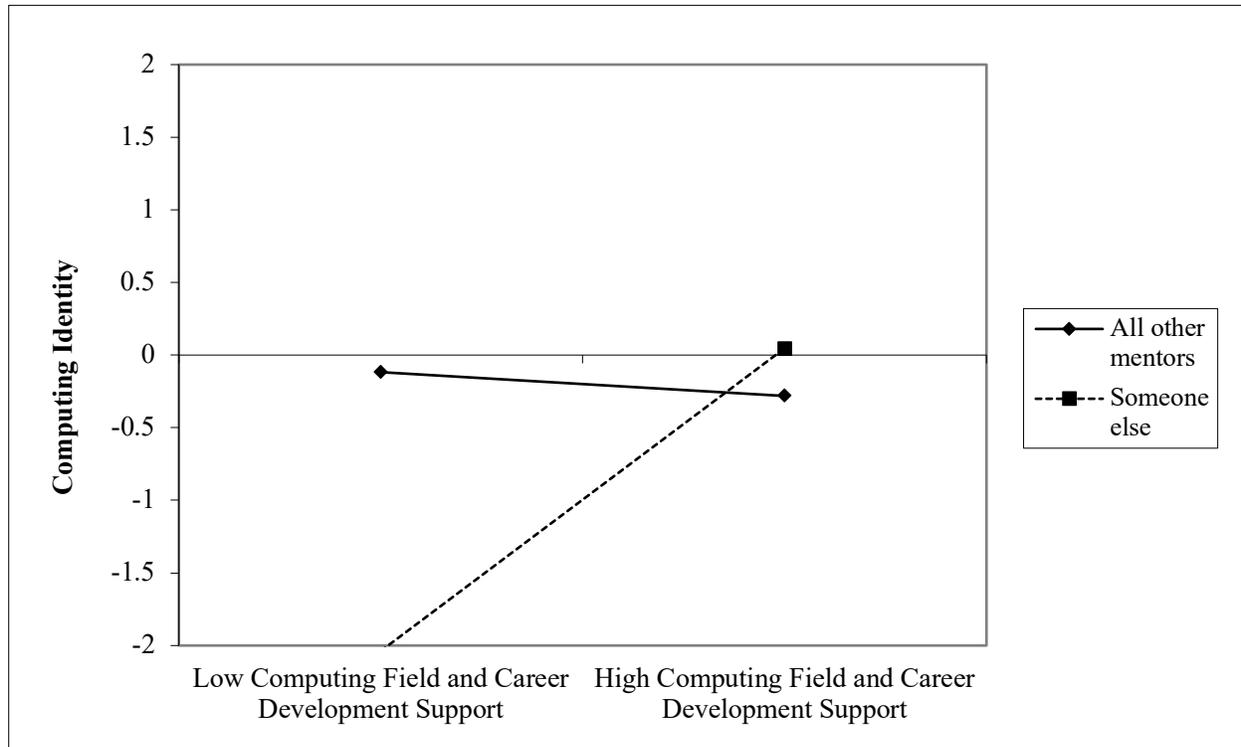
### ***Interaction Effects***

In a second level of inferential analysis, I explored whether the role of mentoring support in predicting psychosocial beliefs was moderated by graduate aspirants' gender, race/ethnicity, or the mentor's role. One significant two-way interaction emerged (Table 6); this conditional effect revealed that, although computing field and career development mentoring support had no significant effect on graduate aspirants' computing identity with most departmental mentors, computing field and career development support significantly predicted computing identity for graduate aspirants mentored by "someone else" in the department (see Figure 2). However, the gap between these two lines is not large, and the slope of the reference group line (i.e., all other departmental mentors) is non-significant. While there may be a significant difference in the benefits gained from being mentored by someone else, the distance between the points in Figure 2 is not wholly sizeable, which may help explain why neither variable was significant as a main

effect. To further investigate who graduate aspirants classified as “someone else,” I explored associated text entries with this option; this revealed that approximately half of graduate aspirants reported friends and alumni of their program that now worked in computing as their primary mentors—a logical connection to providing more beneficial advice when it comes to field-specific mentorship.

**Figure 2**

*Computing Identity by Level of Computing Field and Career Development Mentoring Support Due to Departmental Role of Mentor*



*Note.* Interaction terms were first tested with weighted effect coded variables for gender, race/ethnicity, and mentor's role. Upon generating one significant result, I recoded the significant mentor role (i.e., "someone else") into a dichotomous variable for visual interpretation, with all other departmental mentor roles as the reference group.

## Discussion

Informing the literature on equity in mentorship and graduate school trajectories, this study explored how departmental mentorship in computing shapes the disciplinary psychosocial attributes of undergraduates who aspire to graduate school. Overall, degree completion support (including behaviors where mentors discuss the options and implications of degree choices) positively related to graduate aspirants' computing self-efficacy and identity. The salience of this mentoring support illuminates a focused type of mentorship that may help advance students' decision-making about graduate school. Results also reify the key role of introductory courses, with initial perceptions of computing self-efficacy and identity emerging as the strongest positive

predictors of each outcome. Early general mentoring support during introductory courses, however, negatively related to graduate aspirants' later computing self-efficacy. The array of behaviors measured in general mentoring support during intro courses may be one reason for this counterintuitive result; mentoring conversations are initiated for many reasons and thus may also promote different outcomes, as mirrored in the literature on student-faculty interactions (see Kim & Sax, 2017). As such, it is crucial to delineate greater specificity in mentoring behaviors and understand larger environmental influences that underscore individual interactions.

Employing a critical quantitative lens, the present work extends what is known about mentorship in computing departments by focusing on how the nature and outcomes of mentorship depend on mentors' positional power and students' social identities—two examples of institutional and societal power structures that guide daily interactions, like those in mentor-mentee relationships. The focus on undergraduate computing students who aspire to earn a graduate degree is a novel one, as this pushes the conversation about graduate school trajectories beyond aspirations and into a space that explores what might facilitate students' fulfillment of their aspirations. To date, limited research has discussed computing students' mentoring relationships with an eye toward equity, and this is vital—particularly in the context of graduate school trajectories—if computing departments seek to understand and improve the experiences of historically minoritized students.

While scholars have associated mentoring support and behaviors with undergraduate students' computing self-efficacy and computing identity development (Goh et al., 2007; Hodari et al., 2014), and researchers have explored how mentoring support fosters computing graduate school plans (Charleston et al., 2014; Cohoon et al., 2004; Wofford, 2021; Wofford et al., forthcoming), fewer studies have discussed how such student-level experiences may be a product

of structural and cultural power in computing departments. Using a conceptual perspective of organizational power (Ragins, 1995) with a framework of undergraduate mentorship (Crisp et al., 2017), the current findings shed light on how mentors' positional power and departmental cultural values may complicate graduate aspirants' experiences receiving mentorship in computing departments.

The departmental role (and power) of mentors matters greatly in terms of guiding what support is provided. While some research explores how faculty and peers provide differential mentoring support in computing (Tashakkori et al., 2005), the present study provides new insight by comparing a wider array of mentors' positions. Descriptive results show that graduate aspirants primarily mentored by other students (advanced undergraduates or graduate students) or someone else in the department received more psychological and emotional support, relative to students mentored by faculty members. Recent evidence has suggested that peer mentors can provide key guidance to bolster introductory computing students' confidence (Pon-Barry et al., 2017), which may speak to the psychological support found here. It may also be that computing faculty mentors employ hierarchical power dynamics that serve as a barrier to students receiving emotional support, given that imbalanced power dynamics in student-faculty relationships may be amplified in STEMM (Baber, 2015). Further, computing faculty may feel unequipped to provide psychological and emotional support, as scholars have found that faculty are rarely socialized to view personal support as an essential part of developmental relationships (O'Meara et al., 2013).

Mentors' positional roles also shape computing psychosocial development in this study. Interestingly, having an undergraduate faculty advisor as one's primary departmental mentor was a negative predictor of graduate aspirants' computing self-efficacy, while having another (non-

advisor) faculty mentor was a positive predictor. It is plausible that these other faculty mentors may be PIs of undergraduate research labs or involved in students' computing growth in lieu or in addition to advisors. While the data source used does not allow me to confirm this, I ran additional analyses to explore whether there were differences in the extent to which graduate aspirants perceived mentors to provide research project opportunities, depending on primary mentors' roles. These post-hoc crosstabulations showed significant differences, such that 35.2% of graduate aspirants mentored by another professor reported frequent opportunities to work on a research project, relative to 16.4% of graduate aspirants mentored by faculty advisors. Given the significant association between undergraduate research participation and computing graduate school enrollment (Wright, 2020), this is important context to understand how faculty members who are not students' advisors provide crucial mentoring support that supports self-efficacy.

In alignment with the conceptual framework, it is also imperative to discuss how cultural power in computing departments may influence mentorship. According to Ragins (1995), "the values and norms inherent in an organization's culture can support or deter mentoring relationships" (p. 110). A cultural power perspective is useful when interpreting the finding related to underrepresented Women of Color in computing receiving more psychological and emotional support than underrepresented Men of Color and white men. On one hand, it may be promising that underrepresented Women of Color in computing receive emotional support, as caring attitudes have been supported as a healthy aspect of mentoring relationships for Women of Color in computing (Hodari et al., 2014). Yet, this result also raises concerning questions about whether underrepresented Women of Color in computing report getting more emotional support because of a need for such. Given the persistence of sexism and racism in collegiate computing (e.g., Charleston et al., 2014; Thomas et al., 2018), it may be that these oppressive

environments lead underrepresented Women of Color in computing to seek out emotional support from mentors more frequently than their peers who are men (from any racial/ethnic background). Future research should more directly focus on how disciplinary cultures influence mentoring relationships, as minoritization ensuing from discriminatory norms and values may serve as a substantial barrier to equitable mentorship.

While exploratory, regression analyses also suggest that gendered cultural norms pervade computing departments, mentorship, and relate to the (in)equitable development of computing identity, or the extent to which one feels like a “computing person.” Speaking to extant literature about gender disparities in computing (e.g., Blaney, 2020; Cheryan et al., 2013), findings illustrate that, net of controlled mentorship variables, graduate aspirants who were men held greater levels of computing identity, while women graduate aspirants reported lower levels of computing identity. To further explore these gender differences, I ran independent samples t-tests for mean differences between men and women on computing identity during the introductory computing course and at the time of the follow-up survey (three or four years later). Post-hoc results reveal significant mean differences at each time point ( $p < .001$ ) and identify a larger difference in computing identity between men and women on the follow-up survey (.495) than the introductory course survey (.353). While I am limited in the extent to which these data can discuss *how* gendered cultural values permeate computing departments, the increase in these mean differences over time reveals an increasing gap between men and women graduate aspirants’ beliefs about being a “computing person” and, despite receiving mentorship, women graduate aspirants report lower scores on computing identity than that which they started with. This is a concerning change and suggests that gender disparities remain prominent in computing departments, even when graduate aspirants receive departmental mentorship.

## **Implications**

### **Considerations for Future Research**

The exploratory nature of this study lends itself to many directions for future research. As discussed above, it will be vital for future research to consider how disciplinary cultures and gendered values influence mentoring relationships. Second, a number of mentorship variables may have emerged as non-significant due to the correlation among independent variables. In the present work, I entered regression blocks based on Crisp et al.'s (2017) framework, but different quantitative strategies (e.g., structural equation modeling) may be well-suited to address the relationships among independent variables and measurement invariance between latent constructs. Third, it is crucial to explore the perspectives of mentors in computing departments with quantitative data. While mentees' perceptions illuminate important characteristics of their experiences receiving mentorship, mentors' insights about the extent to which they provide varying forms of support would be useful in creating equity-minded changes to mentoring structures and incentives at a more systemic level. Finally, while exploring affective outcomes among graduate aspirants helps propel research on graduate trajectories into the space between aspiration and matriculation, future research would do well to extend the longitudinal nature of this investigation about mentoring support to disparities in tangible outcomes, such as application and matriculation behaviors, career decisions, and salaries.

### **Implications for Policy and Practice**

Policy- and practice-oriented interventions may help resolve inequities across the quality of graduate aspirants' mentoring relationships in computing. Given the workload necessary to implement the suggestions below (as well as other interventions), and in consideration of how faculty in computing are currently pressed for time and resources (CRA, 2017), computing

departments should consider hiring for a mentoring advocate staff position. This staff member could not only coordinate the institutionalization of policies and practices but could also be a centralized accountability agent for mentors and an advocate for students who may need to switch formalized mentoring relationships. However, to be clear, the establishment of such a staff position should not relieve faculty and other individuals with power in computing departments from learning equity-minded mentoring approaches and advocating for students, especially those with historically minoritized identities.

In light of how mentors' positional roles underscore the nature of support in computing departments, it is vital to ensure equitable access and quality of mentoring relationships across departmental roles. Most importantly, institutions should prioritize structural changes regarding how mentorship is practiced and valued, given that responsibility for ensuring access to and quality within mentorship should not solely fall to the individuals involved. For example, department heads in computing should consider implementing routine "checkpoints" for ethics of care through facilitating departmental dialogues for those serving as mentors. Such dialogues could center on how Gilligan's feminist perspectives about the ethics of care (e.g., a wish to care for and help others, a concern for others and feelings of compassion; see Gilligan, 1977) should apply to developmental mentoring relationships, and dialogues could include self-evaluations for mentors to reflect on their incorporation of these perspectives. Employing ethics of care in mentoring could take several forms including, but not limited to, mentors' regular recognition of mentees' efforts, validation of mentees in humanizing ways, and emotional support of mentees. Notably, while I argue that applying ethics of care in mentorship is an institutional responsibility—as systems of mentorship need to be constructed with care in mind—care is likely to be seen most closely within individual relationships. Yet, researchers have documented

that women faculty spend more time on service- and teaching-related activities than their peers who are men (O'Meara et al., 2017) and that Black women, in particular, provide more psychological support than Black men who are faculty mentors (Griffin & Reddick, 2011). Given these disparities, institutional leaders who are devising “checkpoints” for ethics of care should be wary of relying on women, and especially Black women as well as other Women of Color, to provide care in mentorship more often than men, as this extra weight may have a negative effect on their academic retention or career advancement.

While Gilligan (1977) developed notions about ethics of care as a feminist expansion to stage-based developmental theory, these perspectives may be put in conversation with critical pedagogies and paradigms to make strides in shifting power-laden “norms” that have sustained minoritization in mentoring and computing departments more broadly. For example, ethics of care may provide a powerful way to reframe research-based mentorship in computing through discussions about the role of emotion, care, and subjectivity in research, given that many researchers in computing and other STEMM disciplines falsely hold scientific research to be “value free” and objective (Conefrey, 2001). Further, combining an ethics of care approach with perspectives from critical pedagogies, mentors may be able to hold explicit conversations with mentees about the ways in which knowledge is socially constructed (Monchinski, 2010). One way to concretely implement this type of thinking would be for departments to develop research discussion guides with questions for mentors (as experienced scholars) and mentees (as emerging scholars) to consider how their subjectivities, as well as systems of power, shape research design and interpretations. In turn, departmental support for regular conversations about subjectivity in research and the social construction of knowledge may create more opportunities for historically minoritized students in computing to see themselves as researchers in the field and perhaps

promote their matriculation to graduate school. Additionally, another way to disrupt norms of faculty mentors' power may lie in the institutional inclusion of mentee evaluations (with questions about how ethics of care and critical principles are or are not conveyed through mentorship) as part of faculty members' portfolios for tenure and promotion, similar to the ways that teaching evaluations are currently included. Yet, it is important to bear in mind that mentees may still be hesitant to share honest evaluations of their mentors because of imbalanced power dynamics.

As another structurally-based strategy, computing departments could also incentivize faculty to partner with a graduate student or advanced undergraduate student as a "co-mentor" through supplemental funding (for faculty and student mentors), and departments could then match these co-mentors with a prospective mentee—perhaps a student who has indicated curiosity about graduate school. As such, mentees would gain access to multiple mentors, who would be institutionally incentivized, and benefit from each co-mentor's differential support. In addition, this could serve as an important opportunity to train graduate students and advanced undergraduates—who may be future faculty themselves—as mentors. If these efforts are implemented, they should also be done so with attention to equity, such as leveraging policy that requires mentors and mentees to explicitly discuss reciprocity, expectations, and social positions in cultivating a bi-directional mentoring relationship (Goerisch et al., 2019; NASEM, 2019).

All too often, mentoring is seen as an extra-role responsibility; institutions should work to systematically integrate mentoring opportunities while promoting the value of mentorship (NASEM, 2019). For one, computing departments may consider requiring a monthly "mentoring day," where individuals in the department are given protected time away from daily responsibilities, exposed to equity-focused mentoring resources, and provided structure for

meeting with established or prospective mentors/mentees. While about half of graduate aspirants in this study reported their primary departmental mentor to be their undergraduate faculty advisor or another professor in the computing department, results also showed that faculty have room to grow in their provision of mentoring support (especially psychological and emotional support). Establishing a “mentoring day” through institutional policy and practice may hold the potential to increase faculty training and buy-in for quality mentorship, cultivate more equitable mechanisms of support for all students, and establish a more collaborative culture in computing departments that might, in turn, send signals of inclusion to students who may otherwise be dismayed by the “white and nerdy” stereotypes of computing (see Kendall, 2011).

Finally, specific to graduate school trajectories, this study suggests that some graduate aspirants rely on “someone else” affiliated with their computing department (often friends or alumni) or on graduate students for computing field-specific or psychological and emotional mentoring support. While not the most widely indicated primary mentors, institutional and national policy efforts could articulate partnerships that increase equitable access to mentors who are a “stage-ahead” in undergraduates’ trajectories; otherwise, access to these certain types of mentors could require specific social ties. Institutions may consider hiring a former computing undergraduate student as an “industry liaison” or “graduate school liaison”—even as a part-time consulting role—so that specialized knowledge is equitably available to all graduate aspirants. At the national level, it may also be possible for the Computing Accreditation Commission (ABET, n.d.) to incorporate formalized industry- or graduate-level mentoring partnerships in the curriculum as a seminar course. At the same time, companies or graduate programs sponsoring such mentors should incentivize participation (e.g., through stipends, steps toward promotion).

Formalizing graduate aspirants' access to these types of mentors may be one way that policy and practice can reorient information access about future trajectories with an equity-focused lens.

### **Conclusion**

Attending to graduate aspirants' experiences with mentorship in computing departments, this study reveals new insight about the inequitable nature of mentorship in computing. Results show that graduate aspirants' departmental mentoring support differs based on the mentor's role (e.g., faculty member, advanced peer) and students' social identities—disparities rooted in structural and cultural power, and disparities that may be associated with computing students' realization of their goals to attend graduate school. While mentorship is often thought of as an individual activity, ensuring equitable quality and outcomes of mentoring relationships is also an institutional responsibility in higher education (NASEM, 2019). Mentoring support may be leveraged as a powerful tool to shape students' beliefs about their skills and place in the computing field and developing equity-focused institutional structures of mentorship may be one way to address existing disparities in computing students' development and graduate school trajectories. However, without addressing the complex social structures and dynamics that guide mentoring practices, the promise of mentorship in computing and other STEMM departments may not be fully realized.

## Tables

**Table 1**

*Distribution of Primary Mentors' Roles in Computing Departments (n = 442)*

	Percent
Undergraduate faculty advisor	26.0
Another professor (not faculty advisor)	24.2
Advanced undergraduate peer	17.0
Supervisor or professional colleague	12.9
Academic advising staff	7.0
Someone else	6.8
Graduate student in my department	6.1

**Table 2***Mean Factor Score Differences on Mentoring Support Constructs, by Role of Primary Departmental Mentor*

Mentoring Support Construct	Mean							<i>F</i> statistic; <i>p</i> -value
	Faculty advisor (a)	Other faculty (b)	Advising staff (c)	Undergrad peer (d)	Supervisor, colleague (e)	Graduate student (f)	Someone else (g)	
Psychological and Emotional Support	- 0.249 <sub>dfg</sub>	- 0.268 <sub>dfg</sub>	0.085	0.255 <sub>ab</sub>	0.110	0.338 <sub>ab</sub>	0.675 <sub>ab</sub>	<i>F</i> (6, 428) = 7.939 <i>p</i> < .0001
Degree Completion Support	- 0.071	0.158 <sub>d</sub>	- 0.055	- 0.293 <sub>bg</sub>	- 0.086	0.271	0.416 <sub>d</sub>	<i>F</i> (6, 430) = 3.784 <i>p</i> = .001
Computing Field and Career Development Support	- 0.135	0.100	- 0.310	0.096	- 0.139	0.325	0.203	<i>F</i> (6, 423) = 2.344 <i>p</i> = .031

*Note.* Subscripts indicate significant differences at *p* < .05, detected by examining Tukey post hoc results.

**Table 3***Mean Differences on Psychological and Emotional Support Mentoring Practices, by Gender Identity*

Mentoring Practice	Mean			<i>F</i> statistic; <i>p</i> -value
	Man (a)	Woman (b)	Non-binary (c)	
<i>I have a primary mentor who...</i>				
<b>Psychological and emotional support</b>				
Gives me emotional support	3.28 <sub>b</sub>	3.69 <sub>a</sub>	4.50	$F(2, 435) = 8.788$ $p < .0001$
Encourages me to talk about problems in my social life	3.19	3.41	3.60	$F(2, 436) = 1.941$ $p = .145$
Talks with me about personal issues related to being in the computing major or dept.	3.37	3.40	4.00	$F(2, 434) = 0.854$ $p = .426$
Encourages me to use them as a sounding board to discuss anything	3.56	3.72	4.20	$F(2, 435) = 2.094$ $p = .122$

*Note.* Subscripts indicate significant differences at  $p < .05$ , detected by examining Tukey post hoc results.

**Table 4***Mean Differences on Psychological and Emotional Support Mentoring Practices, by Intersecting Gender and Racial/Ethnic Identities*

Mentoring Practice	Mean						<i>F</i> statistic; <i>p</i> -value
	White man (a)	White woman (b)	Asian man (c)	Asian woman (d)	USOCC man (e)	USOCC woman (f)	
<i>I have a primary mentor who...</i>							
<b>Psychological and emotional support</b>							
Gives me emotional support	3.20 <sub>f</sub>	3.53	3.45	3.63	3.16 <sub>f</sub>	3.94 <sub>ae</sub>	<i>F</i> (5, 423) = 4.004 <i>p</i> = .001
Encourages me to talk about problems in my social life <sup>a</sup>	2.97	3.08	3.45	3.39	3.09	3.77	<i>F</i> (5, 423) = 3.896 <i>p</i> = .002
Talks with me about personal issues related to being in the computing major or dept.	3.35	3.22	3.41	3.34	3.33	3.69	<i>F</i> (5, 422) = 0.802 <i>p</i> = .548
Encourages me to use them as a sounding board to discuss anything	3.63	3.72	3.50	3.64	3.53	3.94	<i>F</i> (5, 422) = 1.271 <i>p</i> = .276

*Note.* Subscripts indicate significant differences at  $p < .05$ , detected by examining Tukey post hoc results.

<sup>a</sup> Homogeneity of variances test was not met for item; thus, differences are not interpretable.

**Table 5**

*Predictors of Computing Self-Efficacy Among Graduate Aspirants with Departmental Mentors in Computing (n = 378)*

Block		Model 1: Main effects		
		Beta	Sig.	
1	Cohort flag	0.02		
	Intro Course Computing Self-Efficacy	0.38	***	
	Early General Mentoring Support	-0.12	*	
2	Race/ethnicity: white	-0.01		
	Race/ethnicity: Asian or Asian American	-0.04		
	Race/ethnicity: Black or African American	0.00		
	Race/ethnicity: Hispanic or Latina/o/x	0.07		
	Race/ethnicity: Arab, Middle Eastern, or Persian	-0.05		
	Race/ethnicity: Multiracial minoritized	-0.03		
	Race/ethnicity: Multiracial white and/or Asian	0.10	*	
	Gender: Man	0.07		
	Gender: Woman	-0.09		
	Gender: Genderqueer, non-binary, non-conforming	0.04		
	Transgender identity: Trans*	-0.02		
	Sexual orientation: Heterosexual	-0.01		
	Sexual orientation: LGBQIA+	0.02		
	Sexual orientation: Prefer not to answer	-0.02		
	First-generation to college status: First generation	0.05		
	Socioeconomic status	0.02		
	Dis/ability status: Disclosed 1+ dis/abilities	-0.01		
	3	Role of mentor: Undergraduate faculty advisor	-0.11	*
		Role of mentor: Another professor (non-advisor)	0.15	**
Role of mentor: Advising staff		-0.06		
Role of mentor: Advanced undergraduate peer		0.03		
Role of mentor: Supervisor or professional colleague		0.01		
Role of mentor: Someone else		-0.03		
Role of mentor: Graduate student		-0.02		
Mentor identity: No identity match		-0.01		
Mentor identity: Gender match only		-0.01		
Mentor identity: Racial or ethnic match only		0.08		
Mentor identity: Gender and racial/ethnic match	-0.05			
4	Duration of relationship with primary mentor	0.09		
	Perception of primary mentor's investment in relationship	-0.03		
5	Psychological and Emotional Support	-0.08		
	Degree Completion Support	0.27	***	
	Computing Field and Career Development Support	0.02		

Note. Adjusted R<sup>2</sup> = 24.0%; \*\*\*  $p < .001$ ; \*\*  $p < .01$ ; \*  $p < .05$ .

**Table 6**

*Predictors of Computing Identity Among Graduate Aspirants with Departmental Mentors in Computing (n = 373)*

Block		Model 1: Main effects		Model 2: Interaction effects	
		Beta	Sig.	Beta	Sig.
1	Cohort flag	0.08		0.08	
	Intro Course Computing Identity	0.44	***	0.43	***
	Early General Mentoring Support	0.06		0.05	
2	Race/ethnicity: white	-0.01		-0.01	
	Race/ethnicity: Asian or Asian American	0.06		0.05	
	Race/ethnicity: Black or African American	-0.03		-0.03	
	Race/ethnicity: Hispanic or Latina/o/x	0.00		0.00	
	Race/ethnicity: Arab, Middle Eastern, or Persian	0.02		0.01	
	Race/ethnicity: Multiracial minoritized	-0.07		-0.08	
	Race/ethnicity: Multiracial white and/or Asian	0.00		0.03	
	Gender: Man	0.18	***	0.17	***
	Gender: Woman	-0.19	***	-0.18	***
	Gender: Genderqueer, non-binary, non-conforming	0.04		0.04	
	Transgender identity: Trans*	0.00		0.00	
	Sexual orientation: Heterosexual	0.01		0.02	
	Sexual orientation: LGBTQIA+	-0.01		-0.02	
	Sexual orientation: Prefer not to answer	-0.01		0.00	
	First-generation to college status: First generation	0.03		0.02	
	Socioeconomic status	0.00		0.00	
	Dis/ability status: Disclosed 1+ dis/abilities	-0.01		-0.02	
3	Role of mentor: Undergraduate faculty advisor	-0.10		-0.10	
	Role of mentor: Another professor (non-advisor)	0.09		0.09	
	Role of mentor: Advising staff	0.03		0.03	
	Role of mentor: Advanced undergraduate peer	0.02		0.03	
	Role of mentor: Supervisor or professional colleague	-0.01		-0.01	
	Role of mentor: Someone else	-0.07		-0.10	
	Role of mentor: Graduate student	0.04		0.03	
	Mentor identity: No identity match	-0.03		-0.03	
	Mentor identity: Gender match only	0.04		0.04	
	Mentor identity: Racial or ethnic match only	-0.03		-0.03	
Mentor identity: Gender and racial/ethnic match	0.01		0.02		
4	Duration of relationship with primary mentor	0.08		0.07	
	Perception of primary mentor's investment in relationship	0.13	*	0.13	*
5	Psychological and Emotional Support	-0.07		-0.07	
	Degree Completion Support	0.13	*	0.16	*
	Computing Field and Career Development Support	0.02		-0.01	
	Computing Field and Career Development Support * Role of mentor: Someone else			0.11	*

Note. Adjusted R<sup>2</sup> for Model 1 = 30.2%; Model 2 = 31.0%; \*\*\*  $p < .001$ ; \*\*  $p < .01$ ; \*  $p < .05$ .

## Appendix

**Table A1**

*Response Rates to BRAID Student Surveys Over Time*

Survey	N Invited	N Respondents	% Response Rate
Pre-test (Beginning of intro course)			
Cohort A	11,944	3,815	31.94%
Cohort B	17,449	4,638	26.58%
Posttest (End of intro course)			
Cohort A <sup>a</sup>	13,643	2,631	19.28%
Cohort B	17,391	2,953	16.98%
Follow-up 1			
Cohort A	4,931	2,103	42.65%
Cohort B	5,442	2,392	43.95%
Follow-up 2			
Cohort A	4,859	1,882	38.73%
Cohort B	5,441	2,128	39.11%
Follow-up 3			
Cohort A	4,851	1,635	33.70%
Cohort B	5,436	1,793	32.98%

*Note.* Response rates reflect responses to individual surveys. To receive an invitation to participate in follow-up surveys, students must have completed *either* the pre-test or posttest.

<sup>a</sup> Overall, more Cohort A students were invited to participate in the posttest than the pre-test, as one BRAID institution did not administer the pre-test, and a different BRAID institution did not administer the posttest.

**Table A2***Profile of Students' Social Identities*

	Percent
<b>Race/ethnicity (n = 437)</b>	
Asian or Asian American	
East Asian or Asian American	18.6
Southeast Asian or Asian American	6.4
South Asian or Asian American	12.4
Asian, Other	0.2
Black or African American	4.6
Hispanic or Latina/o/x	
Mexican	9.2
Puerto Rican	0.7
Latinx, Other	2.7
Arab, Middle Eastern, or Persian	2.7
White	33.6
Multiracial: White, Asian, and/or Asian American only	3.4
Multiracial: Minoritized groups (at least one identity reported as Black, Latina/o/x, Arab, Middle Eastern, or Persian)	5.5
<b>Gender (n = 442)</b>	
Man	67.4
Woman	31.5
Genderqueer, non-binary, or non-conforming	1.1
<b>Transgender (n = 441)</b>	
Cisgender	98.0
Trans*	1.3
Prefer not to answer	0.7
<b>Sexual orientation (n = 436)</b>	
Heterosexual	82.1
Gay	2.8
Lesbian	1.1
Bisexual	7.3
Prefer not to answer	3.9
Not listed; another sexual orientation	2.8
<b>First-generation status (n = 433)<sup>a</sup></b>	
Continuing generation	85.0
First generation	15.0
<b>Socioeconomic status (n = 440)</b>	
Poor	5.7
Below average	15.7
Average	48.9
Above average	27.0

Wealthy	2.7
Dis/ability status (n = 416)	
Disclosed no dis/ability	93.5
Disclosed one or more dis/abilities	6.5
Intersecting racial/ethnic and gender identities (n = 437) <sup>b</sup>	
White men	24.5
White women	8.2
White non-binary	0.9
Asian or Asian American men	24.2
Asian or Asian American women	13.3
Black or African American men	2.7
Black or African American women	1.6
Black or African American non-binary	0.2
Latinx men	8.5
Latinx women	4.1
Arab, Middle Eastern, or Persian men	2.3
Arab, Middle Eastern, or Persian women	0.5
Multiracial: White, Asian, and/or Asian American men	2.1
Multiracial: White, Asian and/or Asian American women	1.4
Multiracial: Minoritized men	3.7
Multiracial: Minoritized women	1.8

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*Note.* American Indian and Native Hawaiian/Pacific Islander were provided as options for race/ethnicity, but no students identifying as such met the filter criteria for this study sample.

<sup>a</sup> First generation includes students from families in which no parent/guardian completed a bachelor's degree.

<sup>b</sup> Students' intersecting racial/ethnic and gender identities are highlighted here due to extant research about gender and racial/ethnic identity concordance in mentorship. Yet, I recognize that many other intersecting identities also contribute to students' daily lived experiences.

**Table A3***Variable Definitions and Coding Scheme*

Variable	Definition/Coding Scheme
<b>Dependent variables (time 2)</b>	
<u>Computing Identity (factor)</u>	
I see myself as a “computing person”	1 = Strongly disagree to 5 = Strongly agree
Computing is a big part of who I am	1 = Strongly disagree to 5 = Strongly agree
I feel like I “belong” in computing	1 = Strongly disagree to 5 = Strongly agree
<u>Computing Self-Efficacy (factor)</u>	
Confidence to become a leader in the field of computing	1 = Strongly disagree to 5 = Strongly agree
Confidence to quickly learn a new programming language on my own	1 = Strongly disagree to 5 = Strongly agree
Confidence to clearly communicate technical problems and solutions to a range of audiences	1 = Strongly disagree to 5 = Strongly agree
<b>Psychosocial and mentoring characteristics during introductory courses (time 1)</b>	
<u>Intro Course Computing Identity (factor)</u>	
I see myself as a “computing person”	1 = Strongly disagree to 5 = Strongly agree
Computing is a big part of who I am	1 = Strongly disagree to 5 = Strongly agree
I feel like I “belong” in computing	1 = Strongly disagree to 5 = Strongly agree
<u>Intro Course Computing Self-Efficacy (factor)</u>	
Confidence to become a leader in the field of computing	1 = Strongly disagree to 5 = Strongly agree
Confidence to quickly learn a new programming language on my own	1 = Strongly disagree to 5 = Strongly agree
Confidence to clearly communicate technical problems and solutions to a range of audiences	1 = Strongly disagree to 5 = Strongly agree
<u>Early General Mentoring Support (factor)</u>	
<i>To what extent did you have a mentor who...</i>	
Helps you improve your computing skills	1 = Not at all to 5 = Very much
Shows compassion for any concerns and feelings you discussed with them	1 = Not at all to 5 = Very much
Shares personal experiences as an alternative perspective to your problems	1 = Not at all to 5 = Very much
Explores career options with you	1 = Not at all to 5 = Very much

## Students' social identities (time 2)<sup>a</sup>

Race/ethnicity<sup>b</sup>

1 = white; 2 = Asian or Asian American; 3 = Black or African American; 4 = Hispanic or Latina/o/x; 5 = Arab, Middle Eastern, or Persian; 6.1 = Multiracial: Minoritized racial or ethnic groups; 6.2 = Multiracial: Asian, Asian American, and/or white

Gender<sup>b</sup>

1 = Man; 2 = Woman; 3 = Genderqueer, non-binary, or non-conforming

Transgender identity

1 = Cisgender; 2 = Transgender

Sexual orientation<sup>b</sup>

1 = Heterosexual; 2 = LGBTQIA+; 3 = Prefer not to answer

First-generation status

0 = Continuing generation; 1 = First generation

Socioeconomic status

1 = Poor; 2 = Below average; 3 = Average; 4 = Above average; 5 = Wealthy

Dis/ability status

0 = Disclosed no dis/ability; 1 = Disclosed one or more dis/abilities

## Relational context (time 2)

Role of mentor<sup>b</sup>

1 = Undergraduate faculty advisor; 2 = Professor at my institution who is not my faculty advisor; 3 = Academic advising staff; 4 = Advanced undergraduate peer; 5 = Supervisor or professional colleague; 7 = Someone else; 8 = Graduate student in my department

Perceived congruence of mentor's gender or racial/ethnic identity<sup>b</sup>

1 = Mentor does not share either identity; 2 = Mentor shares my gender identity only; 3 = Mentor shares my racial/ethnic identity only; 4 = Mentor shares both my gender and racial/ethnic identities

## Mentoring relationship features (time 2)

Duration of relationship with primary mentor

1 = Less than 1 year; 2 = 1-2 years; 3 = 2-3 years; 4 = More than 3 years

Perception of primary mentor's investment

1 = Not at all; 2 = Slightly; 3 = Somewhat; 4 = Quite a bit; 5 = Extremely

## Forms of mentoring support (time 2)

*Referring to your primary mentor, to what extent do (or did) you have someone who regularly:*

### Psychological and Emotional Support (factor)

Gives me emotional support

1 = Strongly disagree to 5 = Strongly agree

Encourages me to talk about problems I am having in my social life

1 = Strongly disagree to 5 = Strongly agree

Talks with me openly about personal issues related to being in my major or dept.

1 = Strongly disagree to 5 = Strongly agree

Encourages me to use them as a sounding board to discuss anything

1 = Strongly disagree to 5 = Strongly agree

Degree Completion Support (factor)

- Helps me realistically examine the degree or certificate options in my field of study 1 = Strongly disagree to 5 = Strongly agree
- Encourages me to consider educational opportunities beyond my current plans 1 = Strongly disagree to 5 = Strongly agree
- Discusses with me the implications of my degree choice 1 = Strongly disagree to 5 = Strongly agree

Computing Field and Career Development Support

- Guides me through a realistic appraisal of my skills 1 = Strongly disagree to 5 = Strongly agree
- Provides practical suggestions for improving my academic performance 1 = Strongly disagree to 5 = Strongly agree
- Encourages me to discuss problems I am having with my coursework 1 = Strongly disagree to 5 = Strongly agree
- Serves as a model for how to be successful in my major or department 1 = Strongly disagree to 5 = Strongly agree

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*Note.* Time 1 reflects variables at the first time point (end of the introductory course), while time 2 reflects variables at the second time point (three or four years after the introductory course).

<sup>a</sup> Social identities were observed at time 2 except first-generation to college status, socioeconomic status, and dis/ability status, as these questions were not asked on the follow-up survey.

<sup>b</sup> Indicates a variable that was weighted effect coded for inferential analyses.

**Table A4***Descriptive Statistics, Factor Loadings, and Reliability*

Block	Variable	Mean or % Within <sup>a</sup>	SD	% Miss.	Factor loadings
	<b>Dependent Variable: Computing Identity (factor; <math>n = 436</math>; <math>\alpha = .854</math>)</b>				
	I see myself as a computing person	4.05	0.991	0.5	0.879
	Computing is a big part of who I am	3.92	1.018	0.9	0.815
	I feel like I belong in computing	3.88	1.022	0.9	0.747
	<b>Dependent Variable: Computing Self-Efficacy (factor; <math>n = 438</math>; <math>\alpha = .751</math>)</b>				
	Confidence in becoming a leader in computing	3.40	1.057	0.7	0.600
	Confidence in quickly learn new programming language	4.10	0.942	0.7	0.805
	Confidence in communicating technical problems	4.03	0.922	0.5	0.740
1	<b>Intro Course Computing Identity (pre-test factor; <math>n = 428</math>; <math>\alpha = .877</math>)</b>				
	I see myself as a computing person	4.11	0.910	1.8	0.841
	Computing is a big part of who I am	3.91	0.978	2.7	0.926
	I feel like I belong in computing	4.04	0.961	2.5	0.758
	<b>Intro Course Computing Self-Efficacy (pre-test factor; <math>n = 428</math>; <math>\alpha = .715</math>)</b>				
	Confidence in becoming a leader in computing	3.47	0.963	2.9	0.654
	Confidence in quickly learn new programming language	3.86	0.941	2.9	0.676
	Confidence in communicating technical problems	3.85	0.837	2.7	0.702
	<b>Early General Mentoring Support (factor; <math>n = 422</math>; <math>\alpha = .912</math>)</b>				
	I have a mentor who helps me improve my computing skills	2.97	1.303	4.1	0.789
	I have a mentor who shows compassion for any concerns and feelings I discussed with them	3.16	1.276	4.5	0.910
	I have a mentor who shares personal experiences as an alternative perspective to my problems	3.07	1.294	4.3	0.916
	I have a mentor who explores career options with me	2.97	1.307	4.1	0.786
2	Gender identity (see Table A2)	–	–	0.0	–
	Transgender identity (see Table A2)	–	–	0.2	–
	Race/ethnicity (see Table A2)	–	–	1.1	–
	Sexual orientation (see Table A2)	–	–	1.4	–
	First-generation status (see Table A2)	–	–	2.0	–

	Socioeconomic status (see Table A2)	3.05	0.873	0.5	—
	Dis/ability status (see Table A2)	—	—	5.9	—
3	Role of primary departmental mentor in computing: % Undergraduate faculty advisor	26.02	—	0.0	—
	Role of primary departmental mentor in computing: % Another faculty member (non-advisor)	24.21	—	0.0	—
	Role of primary departmental mentor in computing: % Academic advising staff	7.01	—	0.0	—
	Role of primary departmental mentor in computing: % Advanced undergraduate peer	16.97	—	0.0	—
	Role of primary departmental mentor in computing: % Supervisor or professional colleague	12.89	—	0.0	—
	Role of primary departmental mentor in computing: % Someone else	6.79	—	0.0	—
	Role of primary departmental mentor in computing: % Graduate student	6.11	—	0.0	—
	Mentor identity concordance: % Shared gender identity only	31.05	—	0.9	—
	Mentor identity concordance: % Shared racial/ethnic identity only	30.14	—	0.9	—
	Mentor identity concordance: % Shared both gender and racial/ethnic identity	15.75	—	0.9	—
	Mentor identity concordance: % Shared neither gender or racial/ethnic identity	23.06	—	0.9	—
4	Duration of relationship with primary mentor	2.56	0.992	0.2	—
	Perception of primary mentor's investment	3.33	1.053	0.7	—
5	<b>Psychological and Emotional Support (factor; <math>n = 435</math>; <math>\alpha = .820</math>)</b>				
	Gives me emotional support	3.42	1.092	0.9	0.819
	Encourages me to talk about problems in my social life	3.26	1.171	0.7	0.834
	Talks with me about personal issues related to being in the computing major or dept.	3.39	1.075	1.1	0.700
	Encourages me to use them as a sounding board to discuss anything	3.62	0.998	0.9	0.569
	<b>Degree Completion Support (factor; <math>n = 437</math>; <math>\alpha = .782</math>)</b>				
	Helps me realistically examine the degree or certificate options in my field of study	3.79	0.953	0.7	0.752
	Encourages me to consider educational opportunities beyond my current plans	3.82	1.022	0.7	0.746
	Discusses with me the implications of my degree choice	3.74	0.955	0.9	0.719
	<b>Computing Field and Career Development Support (factor; <math>n = 430</math>; <math>\alpha = .816</math>)</b>				
	Guides me through a realistic appraisal of my skills	3.61	0.992	1.4	0.725
	Provides practical suggestions for improving my academic performance	3.77	0.911	1.1	0.849
	Encourages me to discuss problems I am having with my coursework	3.73	0.966	1.8	0.762
	Serves as a model for how to be successful in my major or department	3.89	0.877	1.1	0.571

<sup>a</sup> Means are provided for continuous variables; % within each group is provided for categorical variables that are not listed in Table A2 (social identities).

## References

- ABET (n.d.). *Criteria for accrediting computing programs, 2021-2022*. <https://www.abet.org/accreditation/accreditation-criteria/criteria-for-accrediting-computing-programs-2021-2022>
- Aikens, M. L., Robertson, M. M., Sadselia, S., Watkins, K., Evans, M., Runyon, C. R., Eby, L. T., & Dolan, E. L. (2017). Race and gender differences in undergraduate research mentoring structures and research outcomes. *CBE—Life Sciences Education*, 16(2), Article 34. <https://doi.org/10.1187/cbe.16-07-0211>
- Aikens, M. L., Sadselia, S., Watkins, K., Evans, M., Eby, L. T., & Dolan, E. L. (2016). A social capital perspective on the mentoring of undergraduate life science researchers: An empirical study of undergraduate–postgraduate–faculty triads. *CBE—Life Sciences Education*, 15(2), Article 16. <https://doi.org/10.1187/cbe.15-10-0208>
- Anderson, M. K., Anderson, R. J., Tenenbaum, L. S., Kuehn, E. D., Brown, H. K. M., Ramadorai, S. B., & Yourick, D. L. (2019). The benefits of a near-peer mentoring experience on STEM persistence in education and careers: A 2004-2015 study. *The Journal of STEM Outreach*, 2(1). <https://doi.org/10.15695/jstem/v2i1.01>
- AnitaB.org. (n.d.) *BRAID: A diversity program*. <https://anitab.org/braid-building-recruiting-and-inclusion-for-diversity/>
- Annamma, S. A., & Handy, T. (2021). Sharpening justice through DisCrit: A contrapuntal analysis of education. *Educational Researcher*, 50(1), 41-50. <https://doi.org/10.3102/0013189X20953838>
- Baber, L. D. (2015). Considering the interest-convergence dilemma in STEM education. *The Review of Higher Education*, 38(2), 251–270. <https://doi.org/10.1353/rhe.2015.0004>
- Benishek, L. A., Bieschke, K. J., Park, J., & Slattery, S. M. (2004). A multicultural feminist model of mentoring. *Journal of Multicultural Counseling and Development*, 32, 428–442.
- Blake-Beard, S., Bayne, M. L., Crosby, F. J., & Muller, C. B. (2011). Matching by race and gender in mentoring relationships: Keeping our eyes on the prize. *Journal of Social Issues*, 67(3), 622–643. <https://doi.org/10.1111/j.1540-4560.2011.01717.x>
- Blaney, J. M. (2020). Gender and leadership development in undergraduate computing: A closer look at women’s leadership conceptions. *Computer Science Education*, 30(4), 469–499. <https://doi.org/10.1080/08993408.2020.1816769>
- Blaney, J. M., & Stout, J. G. (2017). Examining the relationship between introductory computing course experiences, self-efficacy, and belonging among first-generation college women. *Proceedings of the 48th ACM Technical Symposium on Computer Science Education (SIGCSE '17)*, 69–74. <https://doi.org/10.1145/3017680.3017751>

- Boyer, K. E., Thomas, E. N., Rorrer, A. S., Cooper, D., & Vouk, M. A. (2010). Increasing technical excellence, leadership and commitment of computing students through identity-based mentoring. *Proceedings of the 41st ACM Technical Symposium on Computer Science Education (SIGCSE '10)*, 167–171. <https://doi.org/10.1145/1734263.1734320>
- Bureau of Labor Statistics. (2019). *Occupational outlook handbook: Computer and information technology occupations*. U.S. Department of Labor. <https://www.bls.gov/ooh/computer-and-information-technology/home.htm>
- Byars-Winston, A., & Rogers, J. G. (2019). Testing intersectionality of race/ethnicity × gender in a social–cognitive career theory model with science identity. *Journal of Counseling Psychology*, 66(1), 30–44. <https://doi.org/10.1037%2Fcou0000309>
- Byars-Winston, A. M., Branchaw, J., Pfund, C., Leverett, P., & Newton, J. (2015). Culturally diverse undergraduate researchers' academic outcomes and perceptions of their research mentoring relationships. *International Journal of Science Education*, 37(15), 2533–2554. <https://doi.org/10.1080/09500693.2015.1085133>
- Charleston, L. J. (2012). A qualitative investigation of African Americans' decision to pursue computing science degrees: Implications for cultivating career choice and aspiration. *Journal of Diversity in Higher Education*, 5(4), 222–243. <https://doi.org/10.1037/a0028918>
- Charleston, L. J., Charleston, S. A., & Jackson, J. F. L. (2014). Using culturally responsive practices to broaden participation in the educational pipeline: Addressing the unfinished business of Brown in the field of computing sciences. *The Journal of Negro Education*, 83(3), 400–419. <https://doi.org/10.7709/jnegroeducation.83.3.0400>
- Chemers, M. M., Zurbriggen, E. L., Syed, M., Goza, B. K., & Bearman, S. (2011). The role of efficacy and identity in science career commitment among underrepresented minority students. *Journal of Social Issues*, 67(3), 469–491. <https://doi.org/10.1111/j.1540-4560.2011.01710.x>
- Cheryan, S., Plaut, V. C., Handron, C., & Hudson, L. (2013). The stereotypical computer scientist: Gendered media representations as a barrier to inclusion for women. *Sex Roles*, 69(1-2), 58–71. <https://doi.org/10.1007/s11199-013-0296-x>
- Cheryan, S., Ziegler, S. A., Montoya, A. K., & Jiang, L. (2017). Why are some STEM fields more gender balanced than others? *Psychological Bulletin*, 143(1), 1–35. <https://doi.org/10.1037/bul0000052>
- Cohoon, J. M., Gonsoulin, M., & Layman, J. (2004). Mentoring computer science undergraduates. In K. Morgan, J. Sanchez, C. A. Brebbia, & A. Voiskounsky (Eds.), *Human Perspectives in the Internet Society: Culture, Psychology and Gender* (pp. 199–208). WIT Press.

- Cohoon, J. M., & Lord, H. (2007). Women's entry to graduate study in computer science and computer engineering in the United States. In C. J. Burger, E. G. Creamer, & P. S. Meszaros (Eds.), *Reconfiguring the firewall: Recruiting women to information technology across cultures and continents* (pp. 147–160). AK Peters, Ltd.
- Cole, D., & Espinoza, A. (2011). The postbaccalaureate goals of college women in STEM. *New Directions for Institutional Research*, 2011(152), 51–58. <https://doi.org/10.1002/ir.408>
- Computing Research Association (2017). *Generation CS: Computer science undergraduate enrollments surge since 2006*. <https://cra.org/data/Generation-CS/>
- Conefrey, T. (2001). Sexual discrimination and women's retention rates in science and engineering programs. *Feminist Teacher*, 13(3), 170–192.
- Crisp, G. (2009). Conceptualization and initial validation of the College Student Mentoring Scale (CSMS). *Journal of College Student Development*, 50(2), 177-194. <https://doi.org/10.1353/csd.0.0061>
- Crisp, G., Baker, V. L., Griffin, K. A., Lunsford, L. G., & Pifer, M. J. (2017). Mentoring undergraduate students. *ASHE Higher Education Report*, 43(1), 7–103. <https://doi.org/10.1002/aehe.20117>
- Daly, A., Dekker, T., & Hess, S. (2016). Dummy coding vs effects coding for categorical variables: Clarifications and extensions. *Journal of Choice Modelling*, 21, 36–41. <https://doi.org/10.1016/j.jocm.2016.09.005>
- Davis, S. N., Jacobsen, S. K., & Ryan, M. (2015). Gender, race, and inequality in higher education: An intersectional analysis of faculty-student undergraduate research pairs at a diverse university. *Race, Gender & Class*, 22(3–4), 7–30.
- DiStefano, C., Zhu, M., & Míndrilă, D. (2009). Understanding and using factor scores: Considerations for the applied researcher. *Practical Assessment, Research, & Evaluation*, 14, Article 20. <https://doi.org/10.7275/DA8T-4G52>
- Dugan, J. P., Kusel, M. L., & Simounet, D. M. (2012). Transgender college students: An exploratory study of perceptions, engagement, and educational outcomes. *Journal of College Student Development*, 53(5), 719–736. <https://doi.org/10.1353/csd.2012.0067>
- Flaster, A., Glasener, K. M., & Gonzalez, J. A. (2020). Disparities in perceived disciplinary knowledge among new doctoral students. *Studies in Graduate and Postdoctoral Education*, 11(2), 215–230. <https://doi.org/10.1108/SGPE-05-2019-0053>
- Fryling, M., Egan, M., Flatland, R. Y., Vandenberg, S., & Small, S. (2018). Catch 'em early: Internship and assistantship CS mentoring programs for underclassmen. *Proceedings of the 49th ACM Technical Symposium on Computer Science Education (SIGCSE '18)*, 658–663. <https://doi.org/10.1145/3159450.3159556>

- Gilligan, C. (1977). In a different voice: Women's conceptions of self and of morality. *Harvard Educational Review*, 47(4), 481-517.
- Goerisch, D., Basiliere, J., Rosener, A., McKee, K., Hunt, J., & Parker, T. M. (2019). Mentoring *with*: Reimagining mentoring across the university. *Gender, Place & Culture*, 26(12), 1740–1758. <https://doi.org/10.1080/0966369X.2019.1668752>
- Goh, D., Ogan, C., Ahuja, M., Herring, S. C., & Robinson, J. C. (2007). Being the same isn't enough: Impact of male and female mentors on computer self-efficacy of college students in IT-related fields. *Journal of Educational Computing Research*, 37(1), 19–40. <https://doi.org/10.2190/3705-4405-1G74-24T1>
- Griffin, K. A., & Reddick, R. J. (2011). Surveillance and sacrifice: Gender differences in the mentoring patterns of Black professors at predominantly White research universities. *American Educational Research Journal*, 48(5), 1032–1057. <https://doi.org/10.3102/0002831211405025>
- Hodari, A. K., Ong, M., Ko, L. T., & Kachchaf, R. R. (2014). New enactments of mentoring and activism: U.S. women of color in computing education and careers. *Proceedings of the 10th Annual Conference on International Computing Education Research (ICER '14)*, 83–90. <https://doi.org/10.1145/2632320.2632357>
- Hug, S., & Jurow, A. S. (2013). Learning together or going it alone: How community contexts shape the identity development of minority women in computing. *Journal of Women and Minorities in Science and Engineering*, 19(4), 273–292. <https://doi.org/10.1615/JWomenMinorScienEng.2013005778>
- Hurtado, S., Cabrera, N. L., Lin, M. H., Arellano, L., & Espinosa, L. L. (2009). Diversifying science: Underrepresented student experiences in structured research programs. *Research in Higher Education*, 50(2), 189–214. <https://doi.org/10.1007/s11162-008-9114-7>
- Jacobi, M. (1991). Mentoring and undergraduate academic success: A literature review. *Review of Educational Research*, 61(4), 505–532.
- Kapoor, A., & Gardner-McCune, C. (2018). Understanding professional identities and goals of computer science undergraduate students. *Proceedings of the 49th ACM Technical Symposium on Computer Science Education (SIGCSE '18)*, 191–196. <https://doi.org/10.1145/3159450.3159474>
- Kendall, L. (2011). “White and nerdy”: Computers, race, and the nerd stereotype. *The Journal of Popular Culture*, 44(3), 505–524. <https://doi.org/10.1111/j.1540-5931.2011.00846.x>
- Kim, Y. K., & Sax, L. J. (2017). The impact of college students' interactions with faculty: A review of general and conditional effects. In M. B. Paulsen (Ed.), *Higher education: Handbook of theory and research* (Vol. 32, pp. 85–139). Springer International Publishing. [https://doi.org/10.1007/978-3-319-48983-4\\_3](https://doi.org/10.1007/978-3-319-48983-4_3)

- Kolar, H., Carberry, A. R., & Amresh, A. (2013). Measuring computing self-efficacy. *Proceedings of the 120th ASEE Annual Conference & Exposition*, 1–7.
- Limeri, L. B., Asif, M. Z., Bridges, B. H. T., Esparza, D., Tuma, T. T., Sanders, D., Morrison, A. J., Rao, P., Harsh, J. A., Maltese, A. V., & Dolan, E. L. (2019). “Where’s my mentor?!” Characterizing negative mentoring experiences in undergraduate life science research. *CBE—Life Sciences Education*, 18(4), Article 61. <https://doi.org/10.1187/cbe.19-02-0036>
- Luna, V., & Prieto, L. (2009). Mentoring affirmations and interventions: A bridge to graduate school for Latina/o students. *Journal of Hispanic Higher Education*, 8(2), 213–224. <https://doi.org/10.1177/1538192709331972>
- Lund, T. J., Liang, B., Konowitz, L., White, A. E., & Mousseau, A. D. (2019). Quality over quantity?: Mentoring relationships and purpose development among college students. *Psychology in the Schools*, 56(9), 1472–1481. <https://doi.org/10.1002/pits.22284>
- Mandel, T., & Mache, J. (2017). Examining PhD student interest in teaching: An analysis of 19 years of historical data. *Proceedings of the 48<sup>th</sup> ACM SIGCSE Technical Symposium on Computer Science Education (SIGCSE '17)*, 713. <https://doi.org/10.1145/3017680.3022427>
- McCoy, D. L., Luedke, C. L., Lee-Johnson, J., & Winkle-Wagner, R. (2020). Transformational mentoring practices: Students’ perspectives on practitioner-educators’ support during college. *Journal of Student Affairs Research and Practice*, 57(1), 28–41. <https://doi.org/10.1080/19496591.2019.1614934>
- Miller, A., & Kay, J. (2002). A mentor program in CS1. *ACM SIGCSE Bulletin*, 34(3), 9–13. <https://doi.org/10.1145/637610.544420>
- Monchinski, T. (2010). *Education in hope: Critical pedagogies and the ethic of care*. Peter Lang.
- National Academies of Science, Engineering, and Medicine. (2018). *Graduate STEM education for the 21<sup>st</sup> century*. The National Academies Press. <https://doi.org/10.17226/25038>
- National Academies of Science, Engineering, and Medicine. (2019). *The science of effective mentorship in STEMM*. The National Academies Press. <https://doi.org/10.17226/25568>
- National Center for Science and Engineering Statistics (2019). *Women, minorities, and persons with disabilities in science and engineering: 2019* (NSF Special Report 19-304). National Science Foundation. <https://www.nsf.gov/statistics/wmpd>
- Newman, C. B. (2015). Rethinking race in student-faculty interactions and mentoring relationships with undergraduate African American engineering and computer science majors. *Journal of Women and Minorities in Science and Engineering*, 21(4), 323–346. <https://doi.org/10.1615/JWomenMinorScienEng.2015011064>

- Ogan, C. L., & Robinson, J. C. (2008). “The only person who cares”: Misperceptions of mentoring among faculty and students in IT programs. *Women’s Studies*, 37(3), 257–283. <https://doi.org/10.1080/00497870801917192>
- O’Meara, K., Knudsen, K., & Jones, J. (2013). The role of emotional competencies in faculty-doctoral student relationships. *The Review of Higher Education*, 36(3), 315-347. <https://doi.org/10.1353/rhe.2013.0021>
- O’Meara, K., Kuvaeva, A., Nyunt, G., Waugaman, C., & Jackson, R. (2017). Asked more often: Gender differences in faculty workload in research universities and the work interactions that shape them. *American Educational Research Journal*, 54(6), 1154–1186. <https://doi.org/10.3102/0002831217716767>
- Packard, B. W.-L. (2016). *Successful STEM mentoring initiatives for underrepresented students: A research-based guide for faculty and administrators*. Stylus.
- Pon-Barry, H., Packard, B. W.-L., & St. John, A. (2017). Expanding capacity and promoting inclusion in introductory computer science: A focus on near-peer mentor preparation and code review. *Computer Science Education*, 27(1), 54–77. <https://doi.org/10.1080/08993408.2017.1333270>
- Ragins, B. R. (1995). Diversity, power, and mentorship in organizations: A cultural, structural, and behavioral perspective. In M. M. Chemers, S. Oskamp, & M. Constanzo (Eds.), *Diversity in organizations: New perspectives for a changing workplace* (pp. 91–132). SAGE Publications.
- Ragins, B. R. (1997). Diversified mentoring relationships in organizations: A power perspective. *The Academy of Management Review*, 22(2), 482–521. <https://doi.org/10.2307/259331>
- Rios-Aguilar, C. (2014). The changing context of critical quantitative inquiry. *New Directions for Institutional Research*, 158, 95-107. <https://doi.org/10.1002/ir.20048>
- Robnett, R. D., Nelson, P. A., Zurbriggen, E. L., Crosby, F. J., & Chemers, M. M. (2018). Research mentoring and scientist identity: Insights from undergraduates and their mentors. *International Journal of STEM Education*, 5(1), 41-54. <https://doi.org/10.1186/s40594-018-0139-y>
- Rodriguez, S. L., & Lehman, K. (2018). Developing the next generation of diverse computer scientists: The need for enhanced, intersectional computing identity theory. *Computer Science Education*, 27(3–4), 229–247. <https://doi.org/10.1080/08993408.2018.1457899>
- Rorrer, A. S., Allen, J., & Zuo, H. (2018). A national study of undergraduate research experiences in computing: Implications for culturally relevant pedagogy. *Proceedings of the 49<sup>th</sup> ACM Technical Symposium on Computer Science Education (SIGCSE ’18)*, 604–609. <https://doi.org/10.1145/3159450.3159510>

- Sax, L. J., George, K. L., Wofford, A.M., Sundar, S. (2019, November 14-16). *The tech trajectory: Examining the role of college environments in enhancing a diverse pipeline to computing careers* [Paper presentation]. Association for the Study of Higher Education Annual Meeting, Portland, OR, United States.
- Sax, L. J., & Newhouse, K. N. S. (2019). Disciplinary field specificity and variation in the STEM gender gap. *New Directions for Institutional Research*, 179, 45-71. <https://doi.org/10.1002/ir>
- Singer, N. (2019, January 24). The hard part of computer science? Getting into class. *The New York Times*. <https://www.nytimes.com/2019/01/24/technology/computer-science-courses-college.html>
- Stage, F. K. (2007). Answering critical questions using quantitative data. *New Directions for Institutional Research*, 133, 5-16. <https://doi.org/10.1002/ir.200>
- Stage, F. K., & Wells, R. S. (2014). Critical quantitative inquiry in context. *New Directions for Institutional Research*, 158, 1-7. <https://doi.org/10.1002/ir.20041>
- Sullivan, P., Simmons, M., Moore, K., Meloncon, L., & Potts, L. (2015). Intentionally recursive: A participatory model for mentoring. *Proceedings of the 33rd Annual International Conference on the Design of Communication (SIGDOC '15)*, 1–10. <https://doi.org/10.1145/2775441.2814672>
- Taheri, M., Ross, M. S., Hazari, Z., Weiss, W., Georgiopoulos, M., Christensen, K., Solis, T., Chari, D., & Taheri, Z. (2019). Exploring computing identity and persistence across multiple groups using structural equation modeling. *Proceedings of the 126<sup>th</sup> Annual ASEE Conference & Exposition*, 1-15.
- Taheri, M., Ross, M., Hazari, Z., Weiss, M., Georgiopoulos, M., Christensen, K., Solis, T., Garcia, A., & Chari, D. (2018). A structural equation model analysis of computing identity sub-constructs and student academic persistence. *Proceedings of the 2018 IEEE Frontiers in Education Conference (FIE)*, 1–7.
- Tamer, B., & Stout, J. G. (2016). Understanding how research experiences for undergraduate students may foster diversity in the professorate. *Proceedings of the 47<sup>th</sup> ACM Technical Symposium on Computing Science Education (SIGCSE '16)*, 114–119. <https://doi.org/10.1145/2839509.2844573>
- Tashakkori, R., Wilkes, J. T., & Pekarek, E. G. (2005). A systemic mentoring model in computer science. *Proceedings of the 43rd Annual Southeast Conference (ACM-SE 43)*, 1, 371-375. <https://doi.org/10.1145/1167350.1167453>

- te Grotenhuis, M., Pelzer, B., Eisinga, R., Nieuwenhuis, R., Schmidt-Catran, A., & Konig, R. (2017). When size matters: Advantages of weighted effect coding in observational studies. *International Journal of Public Health*, 62(1), 163–167. <https://doi.org/10.1007/s00038-016-0901-1>
- Thomas, J. O., Joseph, N., Williams, A., Crum, C., & Burge, J. (2018). Speaking truth to power: Exploring the intersectional experiences of Black women in computing. In *Proceedings of the 2018 Research on Equity and Sustained Participation in Engineering, Computing, and Technology (RESPECT)*, 1–8. <https://doi.org/10.1109/RESPECT.2018.8491718>
- Trolian, T. L., & Parker, E. T. (2017). Moderating influences of student–faculty interactions on students’ graduate and professional school aspirations. *Journal of College Student Development*, 58(8), 1261–1267. <https://doi.org/10.1353/csd.2017.0098>
- Williams, M. M., & George-Jackson, C. E. (2014). Using and doing science: Gender, self-efficacy, and science identity of undergraduate students in STEM. *Journal of Women and Minorities in Science and Engineering*, 20(2), 99–126. <https://doi.org/10.1615/JWomenMinorScienEng.2014004477>
- Wofford, A. M. (2021). Modeling the pathways to self-confidence for graduate school in computing. *Research in Higher Education*, 62(3), 359-391. <https://doi.org/10.1007/s11162-020-09605-9>
- Wofford, A. M., Sax, L. J., George, K. L., Ramirez, D., & Nhien, C. (forthcoming). Advancing equity in graduate pathways: Examining the factors that sustain and develop computing graduate aspirations. *The Journal of Higher Education*.
- Wright, H. (2020, February 1). One year later, CERP data still indicate REU participation relates to graduate school enrollment. *Computing Research News*. <https://cra.org/crn/2020/02/one-year-later-cerp-data-still-indicate-reu-participation-relates-to-graduate-school-enrollment/>

**CHAPTER 4:**  
**EQUITY-MINDED STAGE-AHEAD MENTORING: EXPLORING GRADUATE**  
**STUDENTS' NARRATIVES AS MENTORS TO UNDERGRADUATES IN**  
**COMPUTING**

**Introduction**

Enhancing access to and quality within mentoring relationships has become a key priority for U.S. colleges and universities (Crisp et al., 2017). Mentorship holds significant potential to foster undergraduate students' development (Crisp & Cruz, 2009; Jacobi, 1991), and evidence suggests that mentoring can be a critical way to address structural inequities that historically minoritized students face in their educational trajectories (e.g., Dugan et al., 2012; Ong et al., 2011). While scholars have often studied the role of faculty mentorship, a growing body of research has attended to the phenomenon of cascading mentorship (Ahn & Cox, 2016; Blaney et al., 2020). A focus on cascading mentorship, or the process where “postdocs mentor senior graduate students, senior graduate students mentor junior graduate students, and junior graduate students mentor undergraduates” (Golde et al., 2009, p. 57), advances a more robust recognition of mentoring networks. Yet, much remains to be learned about specific types of cascading mentorship, such as that between graduate and undergraduate students.

Graduate-undergraduate mentoring relationships, a phenomenon I call “stage-ahead mentoring,” may be especially vital in disciplines facing exponential growth, such as those in science, technology, engineering, mathematics, and medicine (STEMM). In computing fields, for example, collegiate departments have more than doubled their enrollments since 2009, creating structural challenges such as overenrolled courses and a faculty shortage (Computing Research Association [CRA], 2017). When it comes to managing these challenges, computing departments

are increasingly reliant on graduate student labor to support undergraduate education and often delegate faculty responsibilities (e.g., teaching, advising research) to graduate students (CRA, 2017). In such cases, graduate students' adoption of these faculty-like tasks also opens the door for graduate students to play an additional role—that of mentor to undergraduate students.

By better understanding stage-ahead mentoring in computing, we gain crucial insight into everyday relationships that shape the development of both undergraduate and graduate students. Further, taking an equity-minded lens to stage-ahead mentoring may help computing departments reimagine mentoring support to honor the social identities and contributions of historically minoritized undergraduates (who may be future graduate students) and current graduate students (who may be future faculty), resulting in more equitable mechanisms of support for recruitment and retention. To date, few studies have examined stage-ahead mentorship in computing (Boyer et al., 2010; Tashakkori et al., 2005), nor have scholars explored how graduate students' approaches to mentoring undergraduates may be reflective of their lived experiences and positions within a changing departmental context.

In this qualitative study, I investigate how graduate students make meaning of their experiences as stage-ahead mentors to undergraduates in computing disciplines, focusing on graduate students' notions of identity and equity that influence their approaches to mentoring. As such, I am guided by the following questions:

1. How are mentoring relationships between computing graduate student mentors and undergraduate mentees reflective of and shaped by the social identities of the mentors and mentees?

2. How are mentoring relationships between computing graduate students and undergraduate students shaped by graduate student mentors' perceptions of organizational structures and dynamics?

### **Conceptual Model and Relevant Literature**

The present study is framed by Griffin's (2020) equity-minded mentoring model, or the EM<sup>3</sup>. By foregrounding issues of equity, the EM<sup>3</sup> considers how—despite universities often posing mentorship as a strategy to improve outcomes for all students—mentoring outcomes may not be realized equitably across diverse groups of students. The EM<sup>3</sup> advances an equity-focused approach that calls institutions to create conditions and environments that challenge barriers that have excluded and systemically minoritized<sup>9</sup> potential mentees due to gender, racial, ethnic, sexual, and class identities, among others. At the same time, members of historically minoritized groups have been disproportionately expected to serve as mentors without proper organizational support (Griffin & Reddick, 2011). Thus, if institutions prioritize equity-minded approaches, historically minoritized students may have greater access to high-quality mentoring relationships, mentors may more often engage in culturally relevant practices, and institutional structures may move away from the reproduction of inequitable power in mentoring policies and programs.

In her creation of the EM<sup>3</sup>, Griffin (2020) highlighted how the social identities of mentors and mentees, as well as organizational structures that often bound and guide mentorship, underscore all aspects of mentoring. In particular, Griffin discussed equity in mentoring relationships across four areas: access to mentorship, expectations of who provides mentoring, quality of mentoring interactions, and the role of power dynamics in mentoring. To promote

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<sup>9</sup> I use the terms *minoritized* and *minoritization* to recognize the “process [action v. noun] of student minoritization” (Benitez, 2010, p. 131), referring to the societal construction of minoritization and oppression.

equity in relationship quality and interactions, for example, Griffin asserted that mentors must intentionally honor identity, recognize the power of bias, and cultivate trust—particularly in mentoring historically minoritized individuals. In addition, the EM<sup>3</sup> illustrates how mentoring access and relationship quality determine personal and professional outcomes for mentees and mentors alike.

Guided by the EM<sup>3</sup> (Griffin, 2020), I explored the phenomenon of stage-ahead mentorship that occurs between graduate students and undergraduate students in computing. Specifically, the present study focuses on how social identities and organizational dynamics shape the quality of stage-ahead mentoring relationships. For context, I first review what is known about mentorship in computing, followed by a discussion of the characteristics and outcomes of stage-ahead mentorship in STEMM. Finally, I attend to the importance of considering social identities and larger organizational structures in stage-ahead mentorship, offering insight into the few studies that have documented relevant evidence.

### **Mentorship in Computing Disciplines**

Mentorship is a vital yet understudied component of collegiate computing environments. Among the few studies in computing that have explored mentoring, scholars have largely focused on faculty mentors (Ogan & Robinson, 2008), professional development programs (Hug & Jurow, 2013), or undergraduate peer mentorship (Pon-Barry et al., 2017). Far less is known about stage-ahead mentorship in computing. Graduate students are only one “stage” ahead of undergraduate students, which (as mentors) may make them more accessible and relatable than faculty mentors. Some evidence suggests that graduate students are a crucial to undergraduates’ mentoring networks in computing (Boyer et al., 2010; Tashakkori et al., 2005), making it imperative to better understand the quality of such relationships.

## **Approaches and Outcomes of STEMM Stage-Ahead Mentorship**

The range of practices and approaches used by stage-ahead mentors warrant greater attention. Dolan and Johnson (2009) were among the first to study how postgraduates (i.e., graduate students and postdocs) made meaning of being mentors in life sciences research labs. In this study, Dolan and Johnson documented the benefits postgraduates gain from mentoring, such as greater confidence and productivity, while also noting postgraduates' challenges in building trust and fostering independent thinking with mentees. More recently, Ahn and Cox (2016) explored graduate students' mentoring knowledge, skills, and attributes in engineering research experiences for undergraduates (REUs). According to Ahn and Cox, mentoring knowledge includes familiarity with undergraduates' work and being a helpful resource, mentoring skills emphasizes the interpersonal nature of mentorship (e.g., availability, communication), and mentoring attributes describe character traits of mentors, such as enthusiasm and care.

Graduate students' interactions with undergraduates in STEMM can provide day-to-day support, cultivating mentees' growth in areas such as their self-efficacy (Aikens et al., 2016; Faurot et al., 2013; Thiry & Laursen, 2011). Yet, in formalized lab settings, Packard and colleagues (2014) argued that peer mentors' influence is inhibited by lacking professional authority, compared to faculty mentors. Stage-ahead mentors also positively influence undergraduate students' graduate school or career plans in STEMM (Abbott-Anderson et al., 2016; Campanile, 2015; Dolan & Johnson, 2009). For example, Dolan and Johnson found that postgraduate mentors in the life sciences were able to show undergraduates the type of independent research possible as a graduate student with more advanced skills. Recent evidence has also documented that stage-ahead mentors provide valuable career advice, with graduate students inspiring undergraduates to pursue a career in research (Campanile, 2015). While

scholars have illuminated some detail about the outcomes of STEMM stage-ahead mentoring, it is necessary to explore mentors' approaches further and do so with identity and organizational dynamics in mind—particularly if institutional leaders want to foster equity-minded mentoring.

### **Identity and Organizational Structure in STEMM Stage-Ahead Mentorship**

#### ***Mentors' and Mentees' Social Identities***

It is important to recognize the significant role of mentors' and mentees' social identities in STEMM stage-ahead mentorship (Aikens et al., 2017; Tsai et al., 2013). Researchers must consider how STEMM environments and mentoring relationships can foster students' growth as scientists without undermining the social identities that make students who they are (NASEM, 2019). As Fouad and Santana (2017) noted, not all mentoring relationships operate identically across mentors' and mentees' social identities. For example, in cross-racial mentoring relationships, historically minoritized mentees may have salient racial identities and be paired with a white mentor who is color-evasive and leaves race an undiscussed topic (Thomas, 1993; McCoy et al., 2015). Conversely, mentoring relationships with gender or racial identity concordance may be particularly beneficial for women and Students of Color in STEMM (Blake-Beard et al., 2011; Hodari et al., 2014; Newman, 2015). Scholars have found that shared identities in STEMM mentorship may be critical for women—and particularly Women of Color—as a way to break down barriers of isolation and minoritization within the dominant cultural norms, sexism, or racism in their field (Cohoon et al., 2004; Hodari et al., 2014). Thus, to fully understand the transformative potential or inequities shaped by mentorship in STEMM, it is crucial to consider how social identities impact mentoring relationship quality.

Stage-ahead mentors' identities and backgrounds likely influence their approaches to mentoring undergraduate students, but empirical research has not yet closely explored the extent

to which this may be true. Although Aikens and colleagues (2017) highlighted gender and racial/ethnic identities in mentoring triads between faculty, postgraduates, and undergraduates in the life sciences, the aggregation of identities in this quantitative study limits the depth to which the role of social identities could be understood. Given the growing conversation about STEMM mentors' culturally responsive practices (Byars-Winston et al., 2015; NASEM, 2019), this is an important area that needs to be explored among stage-ahead mentors.

### ***Organizational Structures, Policies, and Practices***

While many facets of stage-ahead mentorship are behavioral in nature, it is necessary to situate our understanding of these relationships within larger organizational dynamics. Broadly speaking, STEMM doctoral students' experiences are situated within a complex system of academic capitalism, including market-like institutional behaviors and views of graduate students as inexpensive labor (Mendoza, 2007; Wofford & Blaney, 2021); consequentially, these systems and norms shape graduate students' daily lives and interactions, including their experiences as mentors. Most work on STEMM stage-ahead mentorship has focused on specific organizational structures, such as REUs (Ahn & Cox, 2016; Aikens et al., 2017; Dolan & Johnson, 2009; Faurot et al., 2013). For example, in chemistry labs at research universities, Andes and Mabrouk (2018) indicated that graduate students act as “surrogate research mentors” to undergraduates (p. 133), navigating ethical dilemmas related to authorship and power. Packard and colleagues (2014) also asserted that, in order for peer mentorship to succeed in STEMM REUs, faculty must grant authority to and signal credibility of peer mentors. Further—although not widely discussed in current studies—graduate students are often TAs or lecturers, during which they engage in the extra role of mentorship but remain subject to the power and preferences of faculty. Extending research on how institutional context affects mentoring (e.g.,

DeAngelo et al., 2016), it is crucial to explore how stage-ahead mentors consider organizational dynamics in their approaches.

### **Addressing the Gap in Knowledge About Graduate Student Mentors**

Taken together, researchers have made inroads into learning how stage-ahead mentors navigate relationships with STEMM undergraduates. Yet, “best practices” for stage-ahead mentors have narrowly focused on REUs (Campanile, 2015; Weigel, 2015). There is also limited research on mentorship in computing (Charleston et al., 2014; Cohoon et al., 2004; Hodari et al., 2014), which is a critical gap given that computing departments face unique challenges relative to other STEMM fields. In particular, computing departments are enduring growing enrollments but continually challenged in recruiting and retaining historically minoritized students. The computing faculty shortage has also contributed to graduate students sometimes doing the “faculty work” of teaching and mentoring (CRA, 2017). Yet, research is even more limited when it comes to the varying sources of mentorship in computing, such as that from advanced peers (Pon-Barry et al., 2017). Graduate students may be key mentors for undergraduates, and by exploring stage-ahead mentors’ approaches with an equity-minded lens, computing departments can better advance a culture of effective, culturally responsive mentoring.

## **Research Design**

### **Methodology**

I use a critical constructivist approach in the present work, a paradigmatic lens that centers how individuals’ ways of knowing are socially, culturally, and historically constructed by one’s experiences (Kincheloe, 2005). Critical constructivism blends elements of constructivist and critical paradigms, collectively framing how knowledge is shaped by individuals’ perceptions as well as broader structures of power (Kincheloe, 2005). By leveraging a critical

constructivist lens, I explore how stage-ahead mentoring interactions are shaped by oppressive structures and organizational power dynamics (discussed further in the analysis section).

Given this study's focus on personal stories of stage-ahead mentors, I used narrative inquiry to design and frame this study. Drawing from a narrative mode of thinking (Bruner, 1986), narrative inquiry "uses stories to understand the meaning of human actions and experiences, the changes and challenges of life events, and the differences and complexity of people's actions" (Kim, 2016, p. 11). Narrative scholars contend that humans act and live through stories, with each individual's experience being at the center of their story, worldview, and interpretation of how their story fits with those of others (Kim, 2016). In education, scholars often use narrative inquiry to organize human experience, focusing on experience as the phenomenon of study (Connelly & Clandinin, 1990; Kim, 2016).

### **Research Site and Participant Sample**

This qualitative study examined the characteristics of stage-ahead mentoring in computing, emphasizing mentors' perspectives on how social identities and organizational structures affect relationship quality. As such, I examined the narratives of graduate mentors in computing at a large, public institution on the west coast, referred to as West Coast University (WCU). WCU is located in a state with state-level bans on affirmative action and is a Minority-Serving Institution. This institution was intentionally selected because the computing school has participated in diversity initiatives and because of their large graduate enrollments in computing-related disciplines. Employing criterion sampling (Maxwell, 2013), I recruited participants who met the following criteria: 1) Identified as a current graduate student in a computing-related discipline at WCU and 2) Identified as a mentor to one or more undergraduate students in a computing-related discipline at WCU. Notably, stage-ahead mentorship may occur in a variety of

formal and informal ways (e.g., through research labs, courses), and I recruited participants broadly to allow for stories spanning these divergent settings.

Recruitment began in spring 2020 by emailing computer science and informatics faculty at WCU, a strategy which connected me with graduate student leaders of an informatics club. The president of the informatics club agreed to disseminate a flyer (see Appendix A) containing a link to a background questionnaire on Qualtrics (<https://www.qualtrics.com>) to graduate students in informatics, and this questionnaire was used to screen for eligibility (see Appendix B). Although this study was not initially bound to a particular computing sub-discipline, I received initial interest from eight informatics Ph.D. students and decided to maintain this disciplinary focus. Due to the decentralized nature of graduate education at WCU, bounding the sample to informatics allowed greater insight about the organizational structures that underscore stage-ahead mentorship. I then used snowball sampling to complete recruitment within the same discipline, asking participants for potential contacts after the first interview.

The final sample included 10 informatics doctoral students. Participants occupied many professional roles at WCU (e.g., TA or lecturer, student officer of organization(s), research assistant) and were at varying stages of doctoral study, ranging from the first to sixth year. Individuals also indicated, both via the background questionnaire and throughout the interviews, a wide array of social and cultural identities with regard to race, ethnicity, gender, sexuality, social class, and other salient identities. Pseudonyms are used throughout this article, and Table 1 provides a profile of the participants in this study.

### **Data Collection and Methods**

Aligning with narrative inquiry, each participant completed an adapted education journey map and two semi-structured interviews. First, participants were given a prompt for creating an

adapted education journey map (Annamma, 2017) prior to the first interview (see Appendix C). Education journey mapping was first introduced as a qualitative methodology for visual narratives, informed by disability critical race theory (DisCrit), critical race spatial analysis, and a sociospatial dialectic (Annamma, 2017). In this study, the use of education journey mapping facilitated participants' ability to make sense of their experiences receiving and providing mentorship in particular physical spaces or temporal stages of their education. Additionally, for participants who hold historically minoritized identities or whose journeys run "counter" to dominant discourses about mentorship, mentoring journey maps allowed them to develop (counter)stories about their engagement in mentorship.

Both semi-structured interviews lasted 60-75 minutes and occurred virtually (on Zoom). To encourage narrative building, the first interview began with participants independently guiding stories about their mentoring journey maps. Subsequently, I shared my own mentoring journey map, as recommended by Annamma (2017). Using maps at the outset of interviews helped establish relationships where participants and I, as the researcher, could discuss similarities and distinctions in our positionalities, and participants often expressed gratitude for the reciprocity that maps cultivated. The remainder of the first interview included open-ended questions to elicit participants' narratives (Kim, 2016). Questions centered on participants' experiences receiving and providing mentorship prior to doctoral study, while also allowing participants to consider how such interactions were reflective of individuals' social identities.

The second interview focused on participants' experiences as stage-ahead mentors during their doctoral studies. Protocol questions were closely aligned with the conceptual framework, covering participants' motivations for and approaches to mentoring, the role of social identities, and the influence of institutional structures or dynamics. This alignment allowed for greater

understanding of how participants' narratives confirm, contest, or extend dimensions of the conceptual framework used in this study. The timing of data collection was especially important in this second interview, as September/October 2020 were characterized by social turmoil related to the COVID-19 pandemic as well as political unrest in the United States. Participants deliberated how mentoring conversations looked before WCU moved to remote learning (in March 2020) and how conversations had changed. Each interview was recorded and transcribed verbatim with participants' consent, with identifying information redacted prior to analysis. See Appendix D for the interview protocols.

### **Analyses**

Analyses centered on narrative meaning among stage-ahead mentors (Polkinghorne, 1988), drawing primarily from interview data to address the research questions. To realize this goal of (re)storying mentors' narratives, I engaged in a three-step analytic process involving pre-coding, categorizing, and connecting strategies. First, both interview transcripts were combined into one file for each participant, which I subsequently uploaded to NVivo for analysis, and data analysis began by reading these collated transcripts. Using pre-coding strategies (Layder, 1998), I began by highlighting relevant aspects of mentors' stories—a practice that I continued throughout analyses to allow for “fluid inquiry” and the representation of mentors' narratives in storied ways (Clandinin & Connelly, 2000).

Next, interviews were coded using a flexible codebook based on Maxwell's (2013) organizational, theoretical, and substantive categorizing distinctions. While organizational categories are most useful to describe the analytic topic (i.e., graduate-undergraduate mentoring relationships in computing), theoretical and substantive categories “identify the *content* of the person's statement or action” (Maxwell, 2013, p. 107) and speak to participants' concepts or

beliefs. Informed by the EM<sup>3</sup> (Griffin, 2020), literature about the qualities of stage-ahead mentorship (see Abbott-Anderson et al., 2016; Ahn & Cox, 2016), and a critical constructivist lens (Kincheloe, 2005), I created three broad theoretical categories:

- (1) Evidence of graduate students cultivating relationships through mentoring knowledge, skills, and attributes
- (2) Evidence of mentors' reflections on their own social identities or those of mentees
- (3) Evidence of systemic and organizational structures, practices, and power dynamics.

Applying these theoretical codes drew my attention to ways that participants constructed their knowledge as social and historical subjects, with an eye toward how stage-ahead mentorship occurs in a complex and power-laden educational system and world. Substantive categorization then transpired by closely reviewing pre-coding notes, engaging in open coding, and iteratively refining inductive codes. Emergent substantive categories illuminated how participants made meaning of their beliefs related to stage-ahead mentorship, such as their mentoring goals and expectations or their observations of how current and prior mentors approached conversations.

After the coding and categorization strategies above, I employed connecting strategies that “look for relationships that *connect* statements and events within a context into a coherent whole” (Maxwell, 2013, p. 113). Re-reviewing transcripts holistically to focus on significant relationships among individuals' experiences aided my ability to re-establish narratives. I also reviewed each participant's mentoring journey map alongside their transcripts to understand how particular mentoring experiences visually fit into the larger temporal and spatial aspects of participants' narratives. Finally, once the categorizing and connecting stages were complete, I

created structured memos and data displays (Miles et al., 2014) to guide my narration and (re)storying of stage-ahead mentors' experiences.

### **Positionality**

As “a process of collaboration involving mutual storytelling between the researcher and the participants” (Kim, 2016, p. 112), narrative inquiry places the researcher as one who (re)tells participants' stories. As such, my positionalities underscored the development and execution of this study. I have long been concerned with graduate students' mentoring practices, evidenced by my initiation of an ambassador outreach program while working in medical graduate admissions and my later role as a stage-ahead mentor during my doctoral training. In conversation with participants, I discussed these professional investments while also explicating the ways my mentoring journey has been shaped by being the first person in my family to earn a graduate degree, by being a white cisgender woman from the midwestern United States, and by my parents' careers in public service. These social identities and values have individual and systemic complexities, and my pathways, privileges, and learned knowledge about mentorship played a key role in navigating this research.

### **Trustworthiness**

Several steps were taken to ensure trustworthiness. First, I maintained a reflective journal, which enabled me to record and grapple with my assumptions, interpretations, and how I emerged as a narrative character alongside my participants (Kim, 2016). Participants were also given full access to and encouraged to review their audio and written files throughout the study. As part of data analysis and member checking, I adapted and facilitated a virtual “cartographer's clinic” (Annamma, 2017) with individual participants, discussing themes and outliers of maps in

to allow for their authentic engagement in the research process. I then clarified findings generated for this work with participants to ensure accuracy of my interpretation.

### **Findings**

In this study, I explored how graduate student mentors in computing considered social identities and organizational dynamics in stage-ahead mentoring with undergraduates. Before introducing the findings, it is important to set the stage in terms of the organizational context for stage-ahead mentoring.

Participants in this study spoke to a range of mentoring contexts. For example, the two most advanced Ph.D. students (Elijah and Olivia) engaged in mentorship as lecturers in the informatics department, while two earlier stage Ph.D. students (Uzo and Val) were interviewed in their first term as teaching assistants (TAs). Several others recounted being mentors as TAs, despite these interactions existing beyond the scope of TA obligations; participants who served as TAs also discussed how mentoring interactions were constrained by the short-term nature of courses. In contrast, some participants developed longer-term mentoring relationships in advisor-run research labs (Diego and Jay) or formalized REUs (Manny and Vicky). While participants spoke to additional stage-ahead mentorship settings beyond research teams and TA experiences (e.g., clubs, conferences), research- and teaching-based mentorship was the most prominent—perhaps speaking to the departmental structures where graduate student labor is most pressing.

The informatics department is one of several computing-related departments at WCU, though associated individuals hold a myriad of foci in their research. Informatics faculty and students necessarily cultivate relationships that span disciplinary boundaries. As Manny, a participant in this study, quipped, "...what is informatics? No one knows what it is, precisely because it is interdisciplinary." Participants in this study were invested in numerous applications

of informatics, such as gender representation in video games, the use of technology in politics, and accessibility design. The variation of participants' interests mirrors the nature of informatics. Broadly speaking, informatics<sup>10</sup> "is a discipline that solves problems through the application of computing or computation, in the context of the domain of the problem" (Groth & MacKie-Mason, 2010, p. 27). At WCU, the departmental website notes that informatics is *everywhere* and, as a field of study, offers a unique window into the relational space between people and technology, exploring what this dynamic means for "our collective future." Doctoral coursework within informatics at WCU helps students consider the broader societal implications of technology; throughout this study, it became clear that the departmental focus on big questions extended into doctoral students' mentoring relationships with undergraduates.

Below, I discuss four emergent themes, each illustrated by doctoral students' stories about providing mentorship. Specifically, stage-ahead mentors' approaches were characterized by identity concordance and discordance, knowledge of institutional and disciplinary minoritization, two-sided negotiation of organizational power dynamics, and organizational limits to providing tangible resources. Together, these themes reveal individual and institutional complexities to fostering equity-minded dimensions of stage-ahead mentorship.

### **Identity Concordance and Discordance**

While reflecting on stage-ahead mentorship, participants considered how identity was present in their relationships. Congruence across demographic social identities as well as deeper-level values offered mentors key opportunities to establish openness and comfort with mentees as they initiated relationships, which then sometimes influenced the ways that mentors facilitated

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<sup>10</sup> Informatics programs also exist under other titles, such as human computer interaction, information science and technology, information technology and informatics, or interactive computing (Groth & MacKie-Mason, 2010).

interactions with their mentees. Further, identity discordance also characterized the quality of stage-ahead mentorship, as mentors reflected on the ways that identity-based differences sometimes increased their awareness of their limitations as mentors or prompted them to alter their approaches in light of identity-based privileges that mentees did not share. Although identity discordance sometimes presented unique challenges in how mentors made meaning of their relational approaches with mentees, such identity-based differences also provided a beneficial avenue for graduate students to center empowerment in their provision of mentorship.

### *Affordance of Identity Concordance*

Seeing mentees' identities that resembled their own, a majority of participants stated that identity-based similarities fostered openness and a more natural connection with mentees. Most mentors felt that identity concordance was especially salient while initiating relationships, seeing how similarities across identities influenced their comfort levels with new mentees. Saanvi, for example, identified as an Indian woman who came to WCU as an international student. When discussing her mentoring interactions that were an extra role beyond TA responsibilities, she said, "I feel I'm just a little more open and comfortable with women...I don't know if my students feel if it comes across. But that definitely plays a role, that I'd be more open with female students." Additionally, Saanvi discussed how her gravitation toward mentoring women may be due to the fact that she was also more comfortable receiving mentorship from women. Where Saanvi felt an implicit affinity toward mentoring (and being mentored by) women, Val discussed initiating conversations where she, as a mentor, was more explicit about her identities, relating:

I see a lot of students who are like me, where their parents are immigrants, their parents don't know how to speak English, and I'm here trying to tell them that, "hey, you know, if I made it here, you certainly can too."

As a queer, Middle Eastern woman whose parents immigrated to the United States, Val elevated her identities as a way to connect with mentees who may share similar lived experiences.

In an equally explicit style, Manny conveyed how he openly discussed his identities—particularly as an international student from Southeast Asia—with mentees “as a mechanism of finding, securing, and developing connections with my mentees, but at the same time being able to extend empathy and also understanding.” Here, Manny reflected how his identities facilitated both initiation and extended connection with his mentees. The way that Manny grounded his empathy in identity concordance was also related by Elijah and Jay, both of whom used identity concordance as a way to shape their mentoring advice about navigating educational resources. Of note, most participants who emphasized the importance of social identity concordance also related that, as mentees themselves, they had prior mentors who shared their social identities (as Saanvi mentioned). Consequentially, having these prior experiences seemed to help participants imagine how they may be mentors in the future.

Interestingly, mentors who noted the role of identity concordance across their “census-level demographic identity” (Elijah) sometimes began their stories by discussing how similarities across values, experiences, and interests (e.g., alignment in political beliefs, being a non-computing undergraduate major) helped form relationships. Half of the participants in this study indicated foregrounding experiential similarities when nourishing new mentoring relationships. For one, Manny expressly sought mentees “who I am fundamentally aligned with.” Min-Sun also

recounted choosing mentees that she “felt sort of kinship to...like they were going through a thing that I was very familiar with.” Deep-level similarities across mentors’ and mentees’ identities, whether expertise-oriented or ideological, ensured participants that they would have an appropriate foundation for stage-ahead mentorship. Collectively, while identity-based similarities were most salient in the initiation stage of stage-ahead mentorship, the narratives above also indicate that identity concordance continued to influence the ways in which mentors guided interactions and the provision of advice based on similar lived experiences.

### *Navigating Identity Discordance*

About half of participants also spoke to identity discordance, or differences across identity, as they cultivated stage-ahead mentoring relationships, which propelled them to “mentor differently depending on people’s identity” (Uzo). Mentors often articulated navigating differences across visible identities, such as race and gender, subsequently conveying how their mentoring approaches across identity-based differences were influenced by their own attributes, experiences, and commitments. Frequently, mentors in this study saw opportunity to navigate around such differences by altering their approaches and offering advice in transparent and empowering ways. Yet, other times, discordance served as a potential barrier to honoring identity in mentoring relationships, either directly or indirectly via mentors’ uncertainty in addressing divergent identities. Reflecting on her identities as an Asian American woman, Vicky noted, “I am trying to share what I know as transparently as I can, and I’m considerate of their background and aware that everybody has different constraints that they’re facing.” Vicky elaborated on how she caveated her guidance in these instances, saying:

I will try to understand that you're different and be like, "okay, well this is what I did, but obviously you can't do the same thing" or like, "I imagine this might help you get past that barrier you have that I didn't have..."

In the example above, Vicky perceived her approach as a transparent one about differences across her identities and those of her mentee. While Vicky explicitly articulated that some of her own strategies may not work for her mentee due to identity discordance, her lack of specificity related to how and why such actions may not be replicable also suggested some discomfort with navigating discordance. Vicky called her approach a less "prescriptive" one, which also aligned with Vicky's own identity, as she articulated her communication style to be an "artifact of my cultural background." Relatedly, Vicky explained contending with cultural microaggressions from people at her prior job who were "supposed to be my mentors;" these interactions "color[ed] sort of everything that happened there" and influenced how she rejected directed guidance. As such, it became clear that Vicky's less prescriptive approach also drew from prior experiences where her cultural identity was devalued in mentoring interactions. Still, through her stories, Vicky seemed to be less adept at navigating identity-related differences in mentoring than other participants, and she appeared to be at an earlier stage of building her consciousness about how such divergence influenced mentoring interactions.

As international students, Diego and Manny also grappled with cultural limitations of their guidance, largely because English was not their primary language and their racial identities were newly salient in the United States (as compared to South America and Southeast Asia, respectively). Discussing how his communication style was shaped by mentoring within an array of cultures, Diego stated being, "more reflective and more careful in the way I want to be

understood and to not be insensitive...I'm also more cognizant of the differences in what the person might understand despite what I'm saying." Manny similarly felt "like I have that additional challenge of being sensitive in terms of how I wield the [English] language." In the temporal context of these interviews (early fall 2020), Diego and Manny also shared that they were grappling with how to mentor in a climate of heightened attention to anti-Black racism in the United States, with each participant making meaning of the limits of their allyship and mentorship given their unfamiliarity with Black students' experiences.

Lastly, several participants were distinctly aware of their identity-based privileges and worked to ensure that they were not amplifying their privileges—a strategy that mentors keenly used to advance inclusion in their relationships and the department. For one, Elijah decentered his dominant racial, gender, and sexual identities because he knew his positionality ascribed systemic power. Elijah discussed applying to be on a panel for prospective graduate students, but "I always made sure that I was not the dominant voice in those discussions...I always try to make sure that if I was sitting on it [the panel], I was the only white dude. Straight white dude." Olivia also noted how she, as a cisgender woman, did not want to assume people's pronouns in her role as a lecturer and mentor for an undergraduate course. As such, Olivia would "use 'they' instead of implying 'he' or 'she' in my emails back and forth with the TA when we're talking about other students" in an effort to disrupt cisgender hegemonic norms aligned with pronoun use. Here, Elijah and Olivia's efforts to shift focus away from their privileges reflect a key part of equity-minded mentoring: alterations of practices by those with systemic power.

### **Knowledge of Institutional and Disciplinary Minoritization**

In discussing how social identities emerged in stage-ahead mentoring interactions, participants often expressed understanding that their considerations of identity were complicated

by the ways that institutional structures and disciplinary cultures governed the minoritization of certain identity groups. More than half of participants in this study told stories about leveraging their knowledge concerning oppressive structures and dynamics in their approaches. Often, this knowledge compelled stage-ahead mentors to bring an increased level of transparency to their relationships with undergraduates and prompted them to direct mentees toward resources that may help them navigate “the goddamn hoops that they have to go through” (Min-Sun).

Transparency was a key aspect of stage-ahead mentors’ approaches, and participants expressed that their honesty was frequently characterized by a growth in their own awareness of imbalanced structural power. As a first-year student, Uzo shared how varying institutional structures or messages were intertwined with their identities as a Nigerian American, asexual, non-binary student. At WCU, Uzo attended a summer program prior to beginning graduate studies, and they highlighted how some of their learned knowledge (and questioning) about the imposter phenomenon was newly crucial to raise in mentoring conversations. Uzo expressed:

It came to my attention that when we talk about imposter syndrome—especially when we’re talking to people who are minoritized in certain communities in STEM—we talk about it like, ‘Oh, you could be more confident, you just need to talk to yourself nicer, everybody’s going through it...’ When we don’t really talk about the fact that it’s there because the institution that we’re in makes us imposters, it’s not in our head. The idea of imposter syndrome kind of gaslights us to think that if we just have a better opinion of ourselves, then we can overcome it. When in reality it’s the institution that needs to treat people better.

Here, Uzo recognized structural minoritization as a contributor to the imposter phenomenon and wanted to convey this to mentees. Uzo's motivation to be transparent aligned with their approach to building relationships, as they shared, "I usually don't attribute people's struggles to their misunderstandings...to the individual, I usually attribute it to the environment that they grew up in or the environment that they exist in now." Diego and Vicky also shared examples of how their learned knowledge about institutional minoritization emerged in their mentoring, with Diego providing advice about challenges for international students and Vicky discussing how she is "reasonably frank" about the "twisted way" that funding committees value personal adversity. Specifically, Vicky recalled being advised to "perform your trauma" in funding applications and, despite feeling unsettled by how institutional norms drove students to parade their experiences of minoritization, felt an obligation to be honest and help mentees learn this information.

On a departmental level, Jay related how minoritization within the school of computing and informatics department shaped the questions they were approached with, and by whom. As a mentor, Jay (who identified as non-binary and queer) had several mentoring interactions with prospective students about climate, saying:

I've had various trans\* students who were thinking about coming into this department email me and be like, 'what's the environment like?'...And I've always been very honest about that... saying, 'well like, I'm not cis, and you're not cis, so I'm going to give you my perspective in an honest way because I think that it's important for you.'

Jay spoke at length about the culture of honesty in their advisor's research lab and how their Ph.D. advisor discussed her barriers (as a queer cisgender woman) in computing fields as well as

the demonstrable power of community for minoritized folx, which prompted Jay to feel that “it’s kind of my duty almost to pass that along, especially to people who might be marginalized in similar ways to me or in different ways to me.” Because of their positionality and knowledge about departmental and disciplinary minoritization, Jay was able to provide advice to prospective trans\* students about the extent to which advisors were accepting and used non-binary pronouns appropriately as well as the departmental value ascribed to research on minoritized groups.

As stage-ahead mentors discussed institutional and disciplinary minoritization, they elaborated on the importance of pointing mentees with minoritized identities toward resources that may help them maneuver exclusionary structures. About one-third of mentors noted learning about resources via institutional training as TAs or graduate students, with Val drawing from this training when she advised two mentees to use the LGBTQ+ center when they disclosed sensitive information to her. Yet, Min-Sun also reflected on the challenges that accompany institutional resources, such as campus accessibility resources, explaining the copious steps and barriers (e.g., documentation, time) she tried to demystify for a mentee. Min-Sun illustrated this mentorship as, “expediting the student toward success to through resources. But, of course, you know, I may give them the information and the information that I give them is already in itself—though it is intended to help—is overwhelming...” Yet, regardless of the challenges institutionalized with certain resources, participants often agreed with Elijah’s sentiment that “calling attention to some of the resources is part of the mentorship.”

### **Two-Sided Negotiation of Organizational Power Dynamics**

Doctoral students occupy a precarious position in the structure of U.S. higher education, often transcending boundaries of student, employee, and educator. These multifaceted roles led participants to perceive having a “mixture of authority” in mentorship, as noted by Olivia, which

can be understood through the ways that they internally and externally negotiated dual realities of organizational power dynamics. Participants ruminated on how their position, as doctoral students, prompted them to teeter between interactions where they held varying levels of power, often creating a sandwiched effect of power in stage-ahead mentorship. On one side, many participants recognized holding a position of greater status or hierarchy while serving as a mentor; this positional power influenced how they adjusted their interpersonal approaches and how they distributed labor in research settings. Such power was further complicated by a few participants, like Min-Sun, perceiving that “a well mobilized undergraduate group has much more power than a single Ph.D. student.” Yet, participants also knew that, relative to their faculty advisor, they still occupied a lower rung on the ladder of organizational power—a position that prompted participants to pick up on cues about mentoring from their Ph.D. advisors and either adopt their advisors’ practices or actively choose to engage in mentorship another way.

As a second-year doctoral student who earned her bachelor’s degree at WCU, Val had a unique perspective about graduate students’ positional power. Val’s trajectory shaped her stage-ahead mentorship, as she mentored undergraduates in a game design club that was pivotal to her own undergraduate success. In fact, when Val decided to pursue her Ph.D. at WCU, members of this club created an advisory role for Val so she could stay involved; yet, Val’s direct transition to graduate school blurred the lines of organizational power for her mentorship. Grappling with these changes, Val said, “as a grad student, I have...a justification as to why I’m a mentor...I have like, I don’t know if status is the right word, but it’s a different status than if I were, you know, in my undergrad.” Val also noted, “a lot of people [in the club] approach me because I’m the most senior—I don’t know how to say that—I’ve been there the longest.” With each of these commentaries, Val’s tone and fragmented language signaled some uneasiness with her seniority.

Val later expressed discomfort that club members had very high expectations for her mentorship, such that she had to approach the club president and say that she was “not an oracle” and was doing her best to advise mentees. While Val was not the only participant navigating new power as the “older experienced party” (Jay), her story depicts an automatic power asymmetry between graduate and undergraduate students that is ascribed by the organizational structure.

In a more formalized setting, such as a research lab, several stage-ahead mentors detailed how hierarchy and power dynamics shaped their navigation of being both a manager and mentor. Participants that mentored in research labs constantly reflected on the workloads they charged their mentees with and recognized, as Elijah put it, being in a “mentorship position of power.” Jay, who worked in a research lab with their Ph.D. advisor, mentored several undergraduate students on research projects related to accessibility in technology. In describing the lab culture, Jay emphasized how intentionality, collaboration, and transparency were values embedded into everyday interactions in the lab—norms that Jay wished to replicate in their own mentorship with undergraduates. Expressing this sentiment, Jay recalled:

When I work with people I, you know, check-in. I’m like, “okay, how’s your workload this week in general? What do you feel like you can take on? If you can’t do this, let me know, and I will do it.” You know, a lot of those kinds of double-checking because I never want someone I’m working with to panic because they feel like they can’t tell me that they’re struggling...

Jay acknowledged that undergraduates were volunteering on the project and wanted to ensure that mentees never felt obligated to overwork, further noting, “if anything, I am beholden to them

for whatever work they can do for me.” These reflections on power and project management also influenced the ways that Jay thought about role modeling in the lab, stating the importance of not “perform[ing] my own busyness.” Jay expounded on how, especially before the COVID-19 pandemic, they held unhealthy habits of overworking, “busy bragging,” and proudly getting insufficient sleep; since then, however, Jay developed new expectations for their mentoring and wanted to provide mentees a balanced perspective about graduate school (and labor norms).

While considering their positional power, Jay also revealed that the lab culture and practices of their Ph.D. advisor shaped their mentoring behaviors. This depicts the complicated dual realities of stage-ahead mentors’ position in the organizational structure. Jay, along with three others (Diego, Val, and Elijah), explicitly stated mirroring mentoring behaviors of their advisors, which speaks to how doctoral students are, in fact, still students, despite absorbing many other responsibilities at universities. For Diego, observing how his Ph.D. advisor prioritized student agency in mentorship was instrumental. Diego reflected that he would often give his “straightforward opinion” to past mentees, directing them in a certain way; however, Diego’s advisor guided conversations by empowering Diego to reflect on a variety of options and choose his own path. After experiencing this approach, Diego expressed that he now tries to “reflect and repeat” his advisor’s style of mentorship.

Notably, stage-ahead mentors did not always adhere to their advisors’ practices. As co-advisees, Manny and Vicky were both afflicted by messaging from their Ph.D. advisor that mentoring and teaching should be a lower priority in graduate school than competitive publications. This “ethos,” as Vicky called it, caused Manny and Vicky to consider how the institution (de)valued their commitment to teaching and mentoring. Manny wrestled with the dissonance between his advisor’s guidance and his own commitment to mentorship, saying,

“...that hinders me, I guess, because now I'm constantly thinking, ‘Okay, am I not playing the game properly?’ And then have to remind myself that I am not playing the game...” Manny elaborated that “it’s easy to get lost in the rat race,” describing how, as an international student from a Southeast Asian country, the neoliberal tendencies of academia in the United States (e.g., individualism, productivity) were significantly different, and more toxic, than the academic culture in which he previously studied and taught. In the end, Manny felt that the misalignment between his beliefs and those of his advisor (as well as the U.S. academic system) served to strengthen his commitment to mentorship and pedagogy. However, he articulated that the mismatch between these values and those which are organizationally rewarded in U.S. higher education compelled him to return to his home country upon completing his Ph.D.

### **Limits and Pivots to Providing Tangible Resources**

As stage-ahead mentors made meaning of how organizational structures, policies, and practices affected mentorship, they sometimes felt constrained in the tangible resources they could provide to mentees. Several participants discussed how institutional resources were bounded, either by perceptions of power and legitimacy or by organizational policy. In turn, mentors felt they were unable to fulfill certain expectations that mentees carried for tangible outcomes of the relationship, such as letters of recommendation, career connections, or funding. In light of these constraints, graduate students sometimes pivoted their provision of mentoring benefits to be more intangible; mentors emphasized how providing mentees with transparent perspectives about their lived experiences, honest assessments of organizational norms and structures, and opportunities for increased agency collectively contributed to mentees’ knowledge and development in less tangible but exceptionally valuable ways. As such, it became

clear that there may be certain approaches to mentoring that doctoral students can uniquely provide to undergraduates.

Across tangible benefits of mentoring relationships, letters of recommendation are a commonly desired outcome. In academia and industry, letters of recommendation are widely regarded and used. As Min-Sun stated, “A reference works as a rung on the scaffolding ladder toward success.” While Min-Sun went on to say that she aims to “offer them [undergraduates] my part of the rung,” she also humorously reflected that “we [doctoral students] don’t have any power to do it [provide recommendations].” Yet, Min-Sun indicated that she may be in a more institutionally legitimized position to provide a reference letter once she becomes the principal investigator of an upcoming research study, as she plans to recruit undergraduate assistance and can “vouch for this person being a very qualified worker.” Min-Sun recognized how recommendations were a tangible form of support that mentees often expected, but she also suggested that references were guarded by a certain level of institutional legitimacy that was rarely obtainable for doctoral students. Similarly, Jay sensed that their institutional power as a graduate student meant that “I can’t necessarily write a letter of recommendation. I don’t even know if...graduate students could do [that].”

The opacity of power and in/tangible outcomes was also sometimes reflected in how participants created stage-ahead mentoring relationships. For one, Elijah discussed mentoring several students in a capstone course, where mentorship was positioned as project-based team learning. Undergraduates in the capstone course were able to opt into a particular team or mentoring experience, of which Elijah’s project was just one possibility. Other options included projects that sponsored by tech industry representatives, and Elijah realized he was limited in the kinds of tangible benefits he could provide, compared to the resources and funding tech

companies had available for mentees. To garner mentees' interest in his project without the industry-based connections or perks, Elijah reframed his project opportunity to be one that centered on mentee agency, leadership, and independence—intangible benefits that were not directly offered in tech companies' mentorship opportunities.

The ways that stage-ahead mentors contended with their organizational power and reframed potential benefits for mentees led Elijah and two others to impart guidance that was perhaps distinctly available because mentors were doctoral students. Min-Sun discussed how, instead of writing recommendations, she tried to “challenge [policies] by empowering people, especially undergraduate students...with teaching them the ways in which administrations talk.” Here, administrative “talk” refers to how university leaders shape policies and practices. Institutional policies are often blurred with complex bureaucratic processes—processes that Min-Sun may have been more familiar with due to transferring institutions multiple times in her own collegiate trajectory. As such, she felt that demystifying these administrative norms with her mentees may help them challenge the institutional status quo to meet their needs. Additionally, funding was a tangible resource that two stage-ahead mentors related being unable to provide due to their lack of organizational power. As an alternative, Olivia leveraged her position as a Ph.D. student to offer transparency about funding stipends. Funding was a common concern for prospective Ph.D. students, and Olivia was frustrated with how other graduate students or faculty “do the workaround when they're not comfortable with the question,” which was often the case at visit days for admitted Ph.D. students. In light of this frustration and her lived experiences navigating funding structures as a Ph.D. student, Olivia wanted to help undergraduates make informed decisions about graduate school by providing them with an honest perspective about monetary organizational affordances and constraints.

## **Summary of Findings**

Exploring stage-ahead mentorship through the narratives of 10 doctoral students studying informatics, a growing sub-field in computing, this study makes significant inroads to understanding graduate students' mentoring approaches with undergraduates. Participants often spoke to considerations of social identities (both their own and those of their mentee), with both visible and deep-level identity dis/similarities reflected in the establishment and cultivation of stage-ahead mentoring. Further, it became clear that considerations of identity and organizational dynamics overlapped when participants discussed using their knowledge about minoritizing institutional and departmental structures or cultures to provide equity-minded guidance to mentees. More organizationally, stage-ahead mentors often shared feeling precarity in the level of power they held as a doctoral student and mentor, navigating higher levels of power as a mentor yet still being mentored themselves. Relatedly, stage-ahead mentors also sometimes felt there were institutional limitations to what outcomes they could provide to mentees because of their status as doctoral students. As such, mentors leveraged their position as doctoral students—and their lived experiences—to engage in unique forms of equity-minded mentorship rooted in empowerment and transparency.

## **Discussion**

Applying Griffin's (2020) equity-minded mentoring model (EM<sup>3</sup>), the present findings build on the notion of cascading mentorship (Golde et al., 2009) and highlight how stage-ahead mentors in computing incorporate equity-minded approaches in their mentoring relationships with computing undergraduates. In particular, participants' stories highlight how the relationship quality of mentoring—a key component of the EM<sup>3</sup>—is underscored by the role of social identities as well as organizational structures and dynamics, as Griffin posited. Indeed, a primary

contribution of this study lies in the strength of these narratives to show how stage-ahead mentors' approaches are not simply a product of individual advice and exchanges; rather, stage-ahead mentorship is reflective of and shaped by complex social systems and dynamics.

For one, these findings reflect the fact that organizational culture has a crucial influence on stage-ahead mentoring. Given that institutional behaviors associated with academic capitalism (e.g., commodification of knowledge, scarcity of resources) shape the everyday lives of STEM graduate students at research universities (e.g., Mendoza, 2007; Wofford & Blaney, 2021), participants' narratives attest that their roles as mentors are no exception. Indeed, many mentors developed stage-ahead relationships through their roles as doctoral students on scientific research teams or labs—a key economic engine at universities (Stephan, 2012). The nature of research-based mentorship speaks to studies on STEM graduate student mentors' practices in REUs (e.g., Ahn & Cox, 2016; Dolan & Johnson, 2009) and confirms their role as “surrogate research mentors” (Andes & Mabrouk, 2018), especially given that mentors were often first connected to their mentees by their overloaded faculty advisors. Yet, these narratives also extend prior work by illuminating how stage-ahead mentors sometimes reject institutional messaging that prioritizes productivity alone, with stage-ahead mentors providing guidance rooted in empathy and empowerment that was often developed through shared identities or lived experiences.

Another key takeaway from this study, and one that is situated in academic capitalism, concerns how stage-ahead mentors wrestled with the nature of power and power dynamics in providing guidance to mentees. While power dynamics are a central concern of the EM<sup>3</sup> (Griffin, 2020), these narratives offer extended clarity as to how power and mentorship are uniquely intertwined depending on the mentor's positional power. Participants were cognizant of their many roles as doctoral students, mentors, workers, and educators, with each role requiring varied

negotiation of power. As discussed by Packard et al. (2014), more senior students (advanced undergraduate mentors, in their study) may struggle with legitimacy in providing mentorship without a certain level of authority granted by their faculty advisor. Stage-ahead mentors' narratives certainly speak to tensions of power and legitimacy in a similar way, but the stakes may be even higher for doctoral students given the nature of Ph.D. reliance on faculty advisors, who often provide funding and can "make or break a Ph.D. student" (Lee, 2008, p. 267). In addition, participants also deliberated how stage-ahead mentorship was intertwined with institutional power. Scholars have asserted that graduate mentors may be pivotal for undergraduates' psychosocial development (e.g., science self-efficacy; Aikens et al., 2016; Faurot et al., 2013; Thiry & Laursen, 2011), which these findings illuminate in terms of mentors' empowerment of undergraduates' agency. Yet, these narratives also complicate such individual support by adding structural nuance, speaking to how doctoral students may be institutionally limited in their provision of tangible resources for mentees, such as letters of recommendation.

These findings also confirm literature that has found identity concordance to be salient through the initiation and cultivation of mentorship (e.g., Blake-Beard et al., 2011; Newman, 2015) and provide evidence to support the notion that "near-peer and peer mentorship models may help provide both deep-level and surface-level matching" (NASEM, 2019, p. 5). More specifically, several participants discussed how gender identity similarities (e.g., identifying as women, identifying as non-cisgender) led to a sense of comfort in forming relationships or providing certain types of mentoring. Such gender similarities have been previously discussed in terms of women receiving more help in STEMM when their mentor shares their gender (Blake-Beard et al., 2011), and the current findings expand our understanding of how such similarities shape day-to-day interactions in nuanced ways. The present work also explores identity

concordance openly, beyond gender and race, which Blake-Beard and colleagues' (2011) implored future researchers to do. Indeed, there are many other individual and intersecting social identities—as well as deep-level similarities across interests, values, and experiences—that stage-ahead mentors reflect upon in their mentoring approaches. Here, findings begin to unearth some of the complex roles that these many identities and experiences play in mentoring processes, while also shedding light on equity-minded ways to navigate identity discordance.

Lastly, aligning with the EM<sup>3</sup> model's consideration of identity and organizational structures in tandem (see Griffin, 2020), the present narratives illustrate how stage-ahead mentors in computing use conversations about identity and minoritization to help mentees counter oppressive cultures, policies, or practices. While Hodari and colleagues (2014) found, from the mentee's perspective, that identity concordance can offer Women of Color beneficial role modeling and community building in computing, the present narratives extend what is known about such role modeling from the lens of stage-ahead mentors. Indeed, stage-ahead mentors often use approaches rooted in transparency and empathy to model how computing undergraduates with historically minoritized identities may be able to navigate oppressive institutional structures, with their motivations often rooted in their own experiences and/or commitments to equity. As such, these findings document that stage-ahead mentoring may be an important form of activism within computing-related departments, one that can be most powerful (in terms of changing oppressive environments at their core) when coupled with actions from individuals who hold greater power in computing departments than do graduate students.

## Implications

### Implications for Theory

While the EM<sup>3</sup> conceptually offers many opportunities to examine the phenomenon of stage-ahead mentoring in computing and other disciplines, there are also several ways this model could be extended. First, the EM<sup>3</sup> may benefit from the addition of macro-level spatial and temporal dimensions. Participants sometimes mentioned differences in their approaches to mentoring depending on the short- or long-term nature of their relationship, mostly when discussing relationships that were adjacent to TA roles (short-term) or in research teams (long-term), which is important to more deeply explore. A second suggestion for applications of the EM<sup>3</sup> concerns the specificity of organizational structures and dynamics. In the present study, participants spoke broadly about institutional and departmental policies or practices that may embolden processes of minoritization. Future research employing the EM<sup>3</sup> would do well to narrow the definition of “organizational structures and dynamics” to more deeply interrogate how particular aspects of the organizational context facilitate or hinder stage-ahead mentoring.

Beyond the EM<sup>3</sup>, several other frameworks may be advantageous to consider in the exploration of stage-ahead mentorship. For one, given the prominence of power and power dynamics in the present study, researchers may consider applying a power-conscious framework (see Linder, 2019) to unearth greater detail about the ways doctoral students navigate power, identity, and activism in being a mentor. Additionally, future scholars might consider using an organizational theoretical approach that attends to disciplinary culture; given that informatics is inherently interdisciplinary in scope, it would be useful to understand the extent to which the equity-minded approaches that emerged from participants’ narratives were a product of the disciplinary culture in which they were earning their doctoral degrees.

## **Implications for Policy and Practice**

Enacting equity-minded stage-ahead mentorship in computing-related fields, and likely in other fields, requires dedicated institutional support for doctoral students and undergraduates to participate in these developmental relationships. Given that stage-ahead mentors discussed using equity-minded mentoring approaches as a strategy to counter harmful policies or practices at departmental or institutional levels, university administrators and faculty should first and foremost interrogate the ways that their existing procedures and ways of operating serve as mechanisms of minoritization (e.g., see a discussion in McGee, 2020) and work towards creating more equitable policies and practices. To be clear, while stage-ahead mentorship may offer ways for doctoral students to guide undergraduates' (counter)navigation of these minoritizing structures, the responsibility for such should not fall to stage-ahead mentors; it is the structures themselves that need to change.

While the pressure to change practice and rewrite policies must come from those in power (i.e., faculty and administrators), university leaders would do well to develop partnerships with stage-ahead mentors in this process. For example, if computing departments strive to cultivate lab environments or REUs, as many do (see Rorrer et al., 2018), there need to be intentional discussions about mechanisms of support in these environments. When it comes to reimagining these support structures, faculty and administrators can learn from stage-ahead mentors by carefully attending to questions such as who carries responsibility for mentoring (at all levels of cascading mentorship between faculty, postdocs, graduate students, and undergraduates), how to set expectations for mentoring, and ways to conduct regular “checkpoints” with care and empathy—all of which need to be built into the organizational culture of the REU. Indeed, if faculty and administrators develop learning environments in

partnership with stage-ahead mentors, they may be able to build collaboration that transcends power dynamics and amplifies graduate students' voices in action-oriented ways. However, two caveats are important to consider with this suggestion. First, decision makers who orchestrate learning environments (like REUs) must convey a vested interest in learning from stage-ahead mentors, especially those who hold historically minoritized identities that have been minimized in STEMM due to systemic racism, cissexism, classism, homophobia, and other interlocking oppressive systems. Second, the pressure to engage in these processes and decisions should not automatically fall on faculty and administrators who have routinely engaged in service-oriented, teaching-intensive, or mentoring activities, as faculty investment in such engagement has disproportionately weighed on women, and particularly Black women (e.g., Griffin & Reddick, 2011; O'Meara et al., 2017).

Within computing departments, it would also be beneficial to incentivize stage-ahead mentors. As shown in this study, informatics doctoral students hold many roles, which may dictate them to prioritize financially or professionally rewarded activities over (uncompensated) mentoring activities. Creating opportunities for Ph.D. students to receive monetary support (via fellowship or supplemental grant for mentoring), course credit, or reserved time for mentoring in research labs or teaching assistantships could go a long way toward institutionalizing value in stage-ahead mentorship. With greater institutional support for Ph.D. students to learn about and practice equity-minded mentoring, stage-ahead mentorship has the potential to provide direct mentoring support for undergraduate student success, important developmental opportunities for graduate students who may soon be faculty or industry leaders, and distribute untenable faculty workloads in rewarding ways. Thus, institutionalized departmental support for stage-ahead mentoring in computing may support academic success at many levels.

Finally, while the suggestions above may address some structural concerns for facilitating stage-ahead mentorship—thus providing greater opportunity for these relationships to grow into their potential—it is also the case that faculty and staff in computing departments should set clear expectations for the role of stage-ahead mentorship. Participants in this study sometimes grappled with power tensions or questions about legitimacy to provide certain types of tangible resources (such as letters of recommendation). As such, departments should set standards for what types of outcomes are valued from graduate student mentors, with institutional messages conveying such expectations to both graduate students and undergraduates. Further, departmental leaders should then encourage stage-ahead mentors to have regular conversations to (re)set expectations and alignment with their mentees, which may be beneficial to creating more robust, longstanding relationships between graduate students and undergraduates in computing.

### **Limitations and Directions for Future Research**

The exploratory nature of this narrative study leaves many opportunities for scholars to continue investigating the phenomenon of stage-ahead mentorship, some of which may address the limitations of the present work. For one, data collection was restricted to a single institution and narratives were derived from doctoral students studying informatics. Thus, researchers may consider examining stage-ahead mentorship across different institutional types or with doctoral students in other STEMM departments and fields of graduate education more broadly, as this could provide necessary in future research, researchers may also be able to execute Annamma's (2017) original vision for the "Cartographer's Clinic" with education journey maps, as anonymity concerns prompted me to adapt this clinic for individual conversations. Third, although the intention was to conduct in-person data collection, the ongoing presence of COVID-19 required virtual data collection. Future studies may consider ethnographic approaches,

especially given that participants' stories about mentoring relationships were reflective in nature, and real-time observations may add depth to understanding mentoring interactions as they occur. Finally, related to the theoretical limitations and implications discussed above, future work may consider more closely attending to spatial context, the temporal nature of relationships, and power-conscious or organizational approaches in stage-ahead mentorship—all of which could illuminate further dimensions of equity-minded mentoring approaches.

### **Conclusion**

As researchers seek to learn more about the phenomenon of cascading mentorship in computing disciplines, it is crucial to consider how stage-ahead mentoring may be a powerful lever to bridge graduate and undergraduate levels of study and promote a culture of equity-minded mentorship. Drawing from the in-depth narratives of 10 informatics doctoral students serving as stage-ahead mentors to undergraduates in computing, this study makes important inroads to understanding the equity-minded dimensions of mentorship that graduate students can engage—specifically concerning social identities as well as organizational structures and dynamics. While findings show great promise in stage-ahead mentorship, there remain crucial steps that colleges and universities can take to institutionalize the value of learning how to mentor in doctoral training across computing-related disciplines like informatics; steps that may be essential to the realization of departmental goals toward equity and inclusion. It is crucial to foster equity-minded mentoring between graduate and undergraduate students at a time when effective and equitable mentorship in STEMM has become a national priority (NASEM, 2019), especially given that many STEMM graduate students have the propensity to become future faculty members and mentor students for decades to come.

**Table 1***Profile of Participants (n = 10)*

Name <sup>a</sup>	Year in Ph.D.	Gender <sup>b</sup>	Race or ethnicity <sup>b</sup>	First-gen status	SES <sup>c</sup>	Int'l student	Undergraduate major(s)
Diego	Second	Man	Latino	No	Below average	Yes	Computer science
Elijah	Sixth	Man	White, Jewish	No	Below average	No	Anthropology
Vicky	Third	Woman	Asian American	No	Average	No	Human computer interaction
Jay	Fourth	Non-binary	White	No	Below average	No	English and informatics
Manny	Third	Man	Southeast Asian	No	Average	Yes	Social sciences and communication
Min-Sun	Third	Woman	Korean	Yes	Poor	No	Management information systems
Olivia	Fifth	Female	White	No	Above average	No	Informatics and computer science
Saanvi	Third	Woman	Indian	No	Average	Yes	Computer science
Uzo	First	Non-binary	Nigerian American	No	Below average	No	Software engineering
Val	Second	Woman	Middle Eastern	Yes	Average	No	Economics

<sup>a</sup> Pseudonyms used for research participants<sup>b</sup> Gender and racial/ethnic identities were self-identified by write-in on the background questionnaire<sup>c</sup> Socioeconomic status (SES) was identified on a 5-point scale from 1=*Poor* to 5=*Wealthy*

**VOLUNTEERS NEEDED FOR UCLA  
RESEARCH STUDY**

**GRADUATE STUDENTS  
IN INFORMATION &  
COMPUTER SCIENCES**

- Are you a current master's or Ph.D. student in ICS?
- Do you regularly engage or have conversations with undergraduate student(s) in ICS?

**IF YES, PLEASE CONSIDER TAKING PART IN A RESEARCH STUDY  
EXAMINING GRADUATE STUDENT MENTORSHIP.**

Study involves:

- Background questionnaire
- Visual activity
- Two interviews (~60 minutes each) via phone/Zoom
- A dialogue with other participants to discuss the visual activity

**PARTICIPANTS WILL BE PAID \$20 FOR  
COMPLETING THE STUDY**

To learn more, please complete a brief  
questionnaire:

**<https://tinyurl.com/UCIGradMentors>**

Questions? Email Annie Wofford  
**[awofford@ucla.edu](mailto:awofford@ucla.edu)**

Appendix B

# Graduate Student Intake Survey

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Q1 Please type your first and last name.

---

Q2 I am at least 18 years of age:

Yes (1)

No (2)

*Skip To: End of Survey If I am at least 18 years of age: = No*

---

Q3 I am currently a graduate student at the UCI Bren School of Information and Computer Sciences (ICS).

Yes (1)

No (2)

*Skip To: End of Survey If I am currently a graduate student at the UCI Bren School of Information and Computer Sciences (ICS). = No*

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Page Break

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Q4 Please select the department in which you are currently pursuing your degree.

Computer Science (1)

Informatics (2)

Statistics (3)

Q5 Please select the name of the degree that you are currently pursuing.

- Master of Computer Science (M.C.S.) (1)
  - Master of Science (M.S.) in Computer Science (2)
  - Doctor of Philosophy (Ph.D.) in Computer Science (3)
  - Graduate Program in Networked Systems (M.S. and Ph.D.) (4)
  - Graduate Program in Mathematical, Computational, and Systems Biology (5)
  - Other graduate degree in the Department of Computer Science (6)
  - Master of Human Computer Interaction and Design (7)
  - Master of Science (M.S.) in Informatics (8)
  - Doctor of Philosophy (Ph.D.) in Informatics (9)
  - Master of Software Engineering (10)
  - Master of Science (M.S.) in Software Engineering (11)
  - Doctor of Philosophy (Ph.D.) in Software Engineering (12)
  - Other graduate degree in the Department of Informatics (13)
  - Master of Science (M.S.) in Statistics (14)
  - Doctor of Philosophy (Ph.D.) in Statistics (15)
  - Other graduate degree in the Department of Statistics (16)
-

*Display This Question:*

*If Please select the name of the degree that you are currently pursuing. = Other graduate degree in the Department of Computer Science*

*Or Please select the name of the degree that you are currently pursuing. = Other graduate degree in the Department of Informatics*

*Or Please select the name of the degree that you are currently pursuing. = Other graduate degree in the Department of Statistics*

Q6 You selected that you are pursuing another graduate degree than the options provided. Please type the name of the degree you are currently seeking:

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Q7 What is your current class standing (for the 2020-2021 academic year) in your degree program?

- First year (1)
- Second year (2)
- Third year (3)
- Fourth year (4)
- Fifth year (5)
- Other; please specify: (6) \_\_\_\_\_

End of Block: Introduction

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Start of Block: Mentoring Role

Q8 Do you regularly engage or have conversations with undergraduate student(s) in ICS? These conversations could be in a formal role (e.g., as a Teaching Assistant, member of a research lab) or an informal way (e.g., through student clubs, ICS events, or peer relationships).

- Yes (1)
- No (2)
- Not sure (3)

---

Q9 Check the activities that you engage in **with an undergraduate student in ICS** from the list below. Please select all that apply.

- Provide emotional support (1)
  - Express confidence in their academic ability (2)
  - Talk with them about personal issues related to being in ICS (3)
  - Encourage them to think about pursuing graduate school (4)
  - Help them work toward achieving their academic aspirations (5)
  - Encourage them to perform to the best of their abilities in classes (6)
  - Encourage them to discuss problems they have with computing coursework (7)
  - Share personal examples of difficulties you have had to overcome to accomplish academic goals (8)
  - Something else; please specify: (9)
-

End of Block: Mentoring Role

---

Start of Block: Additional Demographic Information

Q10 How would you describe your race/ethnicity? Please type below.

---

Q11 How would you describe your gender identity (e.g., woman, non-binary, man, etc.)? Please type below.

---

Q12 Please indicate your gender pronoun(s) below.

she/her/hers (1)

he/him/his (2)

they/them/theirs (3)

ze/hir/hirs (4)

Not listed; please specify: (5)

---

Q13 How would you describe your socioeconomic status?

- Poor (1)
  - Below average (2)
  - Average (3)
  - Above average (4)
  - Wealthy (5)
- 

Q14 Do you consider yourself a first-generation college student? I define "first-generation college student" to mean that none of your parent(s) or guardian(s) attended college.

- Yes (1)
  - No (2)
- 

Page Break

---

Q15 Please type your preferred email below.

---

End of Block: Additional Demographic Information

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## Appendix C

### Mentoring Journey Map Prompt (Adapted from Annamma, 2017)

Using visual drawings (e.g., markers, pens on white paper), map your education journey from when you started school to now, focusing on mentorship that you have received or provided. Include people, places, communities, barriers, and opportunities related to mentorship on the way. Draw your interactions with mentors and/or mentees at school and elsewhere, including positive and negative experiences related to your education journey. You can use different colors to show different feelings, and you can use symbols like lines and arrows or words. These are just suggestions. Be as creative as you like and, if you don't want to draw you can make more of a flowchart. You will get a chance to explain your map to me in the first interview and discuss with other participants at the end of the study.

## Appendix D

### Interview 1: Mentoring Journey Map Debrief Protocol

*As a semi-structured interview, these are guiding questions. During the interview, questions may follow a different order, be less relevant and thus not asked, or follow-up questions may emerge.*

---

#### **Part I – Background and Introduction to Topic**

1. Introductions – reminder of confidentiality; pseudonym; ask if there are any changes in the language used to identify themselves in the questionnaire; informed consent (start recording and state date/time)
2. First, before talking in depth about mentorship, I'd like to establish a baseline for what you mean. How would you define mentorship?
  - a. *Probe:* Think about people that may have come to mind when you drew your mentoring journey map. What kinds of behaviors did these people engage in (or not)?

#### **Part II – Debriefing the Mentoring Journey Map**

3. Can you walk me through your mentoring journey map? Guide me through your mentorship experiences—both beneficial and challenging. I will also share my map.
  - a. What would you say has been the most formative experience you have had receiving mentorship in your educational journey? What made this so impactful?

#### **Part III – Prior Experiences Receiving Mentorship**

4. How have your **own** identities (e.g., gender, racial/ethnic, class, dis/ability, sexuality, etc.) and family backgrounds shaped your experiences as a mentee?
5. How have your **mentors'** identities (e.g., gender, racial/ethnic, class, dis/ability, sexuality, etc.) shaped your experiences as a mentee?
6. Transition to graduate school:
  - a. When did you know you wanted to pursue graduate school?
  - b. Tell me about your decision-making process to come to WCU. How did you get here? Did you have a mentor in this process?

7. Mentors in computing:
  - a. How have your prior mentors influenced your computing experiences?
  - b. When you were an undergraduate (or before), did you know any graduate students in computing? Tell me more, if so.
8. *Probes, quality of mentorship*:
  - a. How would you describe the quality of the mentorship you've received?
  - b. Can you tell me about a challenging or difficult experience you've had with a mentor, if you've had one?
    - i. Did this challenging experience change the nature of the way you interacted with this mentor?

**Part IV – Prior Experiences as a Mentor** (OPTIONAL – If map reveals they have served as a mentor before grad school)

I now have a few questions about your experiences **providing mentorship**. Think about the times you have been a mentor before graduate school.

9. How have your **own** identities (gender, racial/ethnic, dis/ability, class, etc.) and family backgrounds shaped your prior experiences as a mentor?
10. How have your **mentees'** identities (e.g., gender, race/ethnicity, sexual orientation, first-generation status) shaped your prior experiences as a mentor?
11. Transition to graduate school:
  - a. Did your prior experience serving as a mentor informed your decision to apply to graduate school? If so, how?
  - b. How have your former mentees influenced your experiences in computing?

**Part V – Wrap-Up**

12. What thoughts do you have about this educational journey mapping activity? Is there anything I didn't ask that you'd like to add?

## Interview 2: Follow-Up Interview Protocol

*As a semi-structured interview, these are guiding questions. During the interview, questions may follow a different order, be less relevant and thus not asked, or follow-up questions may emerge.*

---

### **Part I – Direct Follow Up from Interview I**

1. Reminders of confidentiality; ask if there are any changes in the language you used to identify themselves in the questionnaire (start recording and state date/time)
2. (If clarification is needed): In your first interview, you mentioned \_\_\_\_\_ (e.g., detail, timeline, order of events). Can you tell me more about that?
3. Looking at the map you drew before, is there anything else you would add, having had time to think more about mentorship in your educational journey? Explain.

### **Part II – Experiences as a Stage-Ahead Mentor**

1. How would you describe your motivation for being a mentor during graduate school?
  - a. *Probes:*
    - i. How has mentorship that you have previously received informed your decision to become a mentor in graduate school? What about your experiences being a mentor before graduate school?
    - ii. Can you think of any experiences, outside of prior mentoring, shaped your desire to become a mentor in graduate school?
2. Do you think your social and cultural identities or family background played a role in your decision to become a mentor as a graduate student? If so, how?
3. Do you think there are benefits to being a graduate student mentor? If so, tell me about them. What about challenges to serving as a mentor?

### **Part III –Mentoring Before the COVID-19 Pandemic**

4. How did you build a mentoring relationship with your mentee? (e.g., how did you meet)
5. Prior to the closure of campuses, what were the core elements of mentoring conversations you had with your mentee(s)? Be as specific as possible (e.g., did you give feedback on work, advisor relationships, goal setting, personal growth, **computing skill growth, plans for graduate school**, place and frequency of meetings).

- a. Follow-up questions as needed

#### **Part IV – Mentoring During the COVID-19 Pandemic**

6. We are currently living in a time where individuals and institutions are attending to the COVID-19 pandemic and structural anti-Black racism.
  - a. What are some of the major ways that the COVID-19 pandemic and civil unrest about structural racism have impacted you personally and as a graduate student?
  - b. What impact has there been on your experiences as a mentor? Can you talk about any changes you have seen in the core elements of your mentoring conversations?

#### **Part V – Mentoring Identity**

7. I now have a few questions about specific aspects of your experiences you just shared.
  - a. Thinking about your time being a mentor in grad school, what do you expect of yourself in this role?
  - b. What do you think your mentee expects of you? How did you learn this?
  - c. Do you think your social and cultural identities influence the way you mentor? How?
  - d. Do you think the campus environment, policies, or practices impact how you mentor?
  - e. In your first interview, you talked about mentorship you've received from \_\_\_\_\_. In what ways do your approaches as a mentor reflect (or not) the mentoring that you have received?

#### **Part VI – Wrap-Up and Future Research**

8. Is there anything that I didn't ask about that you would like to add?
9. Are there any materials you have used in being a mentor as a graduate student (e.g., training materials, CV examples)? Would you be willing to share these with me?

I will send you a summary of findings, which you have no obligation to respond to, but feedback is welcome. Would you participate in future research if contacted again?

## References

- Abbott-Anderson, K., Gilmore-Bykovskiy, A., & Lyles, A. A. (2016). The value of preparing PhD students as research mentors: Application of Kram's temporal mentoring model. *Journal of Professional Nursing, 32*(6), 421-429. <https://doi.org/10.1016/j.profnurs.2016.02.004>
- Ahn, B., & Cox, M. F. (2016). Knowledge, skills, and attributes of graduate student and postdoctoral mentors in undergraduate research settings. *Journal of Engineering Education, 105*(4), 605–629. <https://doi.org/10.1002/jee.20129>
- Aikens, M. L., Robertson, M. M., Sadselia, S., Watkins, K., Evans, M., Runyon, C. R., Eby, L. T., & Dolan, E. L. (2017). Race and gender differences in undergraduate research mentoring structures and research outcomes. *CBE—Life Sciences Education, 16*(2), Article 34. <https://doi.org/10.1187/cbe.16-07-0211>
- Aikens, M. L., Sadselia, S., Watkins, K., Evans, M., Eby, L. T., & Dolan, E. L. (2016). A social capital perspective on the mentoring of undergraduate life science researchers: An empirical study of undergraduate–postgraduate–faculty triads. *CBE—Life Sciences Education, 15*(2), Article 16. <https://doi.org/10.1187/cbe.15-10-0208>
- Andes, A., & Mabrouk, P. A. (2018). Authorship in undergraduate research partnerships: A really bad tango between undergraduate protégés and graduate student mentors while waiting for Professor Godot. In P. A. Mabrouk & J. N. Currano (Eds.), *ACS Symposium Series, 1291* (pp. 133-158). American Chemical Society.
- Annamma, S. A. (2017). Disrupting cartographies of inequity: Education journey mapping as a qualitative methodology. In D. Morrison, S. A. Annamma, & D. D. Jackson (Eds.), *Critical race spatial analysis: Mapping to understand and address educational inequity* (pp. 35–50). Stylus Publishing, LLC.
- Benitez, M., Jr. (2010). Resituating culture centers within a social justice framework: Is there room for examining Whiteness? In L. D. Patton (Ed.), *Culture centers in higher education: Perspectives on identity, theory, and practice* (pp. 119-134). Stylus.
- Blake-Beard, S., Bayne, M. L., Crosby, F. J., & Muller, C. B. (2011). Matching by race and gender in mentoring relationships: Keeping our eyes on the prize. *Journal of Social Issues, 67*(3), 622–643. <https://doi.org/10.1111/j.1540-4560.2011.01717.x>
- Blaney, J. M., Kang, J., Wofford, A. M., & Feldon, D. F. (2020). Mentoring relationships between doctoral students and postdocs in the lab sciences. *Studies in Graduate and Postdoctoral Education, 11*(3), 263-279. <https://doi.org/10.1108/SGPE-08-2019-0071>

- Boyer, K. E., Thomas, E. N., Rorrer, A. S., Cooper, D., & Vouk, M. A. (2010). Increasing technical excellence, leadership and commitment of computing students through identity-based mentoring. *Proceedings of the 41st ACM Technical Symposium on Computer Science Education (SIGCSE '10)*, 167-171. <https://doi.org/10.1145/1734263.1734320>
- Bruner, J. S. (1986). *Actual minds, possible worlds*. Harvard University Press.
- Byars-Winston, A. M., Branchaw, J., Pfund, C., Leverett, P., & Newton, J. (2015). Culturally diverse undergraduate researchers' academic outcomes and perceptions of their research mentoring relationships. *International Journal of Science Education*, 37(15), 2533–2554. <https://doi.org/10.1080/09500693.2015.1085133>
- Campanile, M. F. (2015). *The impacts and "best practices" of undergraduate - graduate student mentoring relationships in undergraduate research experiences* (Publication No. 10007520) [Doctoral dissertation, Illinois Institute of Technology]. ProQuest Dissertations and Theses Global.
- Charleston, L. J., Charleston, S. A., & Jackson, J. F. L. (2014). Using culturally responsive practices to broaden participation in the educational pipeline: Addressing the unfinished business of Brown in the field of computing sciences. *The Journal of Negro Education*, 83(3), 400-419.
- Clandinin, D. J., & Connelly, F. M. (2000). *Narrative inquiry: Experience and story in qualitative research*. Jossey-Bass.
- Cphoon, J. M., Gonsoulin, M., & Layman, J. (2004). Mentoring computer science undergraduates. In K. Morgan, J. Sanchez, C. A. Brebbia, & A. Voiskounsky (Eds.), *Human perspectives in the internet society: Culture, psychology and gender* (pp. 199–208). WIT Press.
- Computing Research Association (2017). *Generation CS: Computer science undergraduate enrollments surge since 2006*. <https://cra.org/data/Generation-CS/>
- Connelly, F. M., & Clandinin, D. J. (1990). Stories of experience and narrative inquiry. *Educational Researcher*, 19(4), 2-14.
- Crisp, G., Baker, V. L., Griffin, K. A., Lunsford, L. G., & Pifer, M. J. (2017). Mentoring undergraduate students. *ASHE Higher Education Report*, 43(1), 7–103. <https://doi.org/10.1002/aehe.20117>
- Crisp, G., & Cruz, I. (2009). Mentoring college students: A critical review of the literature between 1990 and 2007. *Research in Higher Education*, 50(6), 525–545. <https://doi.org/10.1007/s11162-009-9130-2>

- DeAngelo, L., Mason, J., & Winters, D. (2016). Faculty engagement in mentoring undergraduate students: How institutional environments regulate and promote extra-role behavior. *Innovative Higher Education*, 41(4), 317–332. <https://doi.org/10.1007/s10755-015-9350-7>
- Dolan, E., & Johnson, D. (2009). Toward a holistic view of undergraduate research experiences: An exploratory study of impact on graduate/postdoctoral mentors. *Journal of Science Education and Technology*, 18(6), 487-500. <https://doi.org/10.1007/s10956-009-9165-3>
- Dugan, J. P., Kusel, M. L., & Simounet, D. M. (2012). Transgender college students: An exploratory study of perceptions, engagement, and educational outcomes. *Journal of College Student Development*, 53(5), 719–736. <https://doi.org/10.1353/csd.2012.0067>
- Faurot, M. E., Doe, F., Jacobs, E. R., Lederman, N. G., & Brey, E. M. (2013). From the undergraduate student perspective: The role of graduate students in an undergraduate research program. *Proceedings of the 120th ASEE Annual Conference & Exposition*, 1–12.
- Fouad, N. A., & Santana, M. C. (2017). SCCT and underrepresented populations in STEM fields: Moving the needle. *Journal of Career Assessment*, 25(1), 24–39. <https://doi.org/10.1177/1069072716658324>
- Golde, C. M., Bueschell, A.C., Jones, L., & Walker, G.E. (2009). Advocating apprenticeship and intellectual community: Lessons from the Carnegie Initiative on the Doctorate. In R. G. Ehrenberg, & C. V. Kuh (Eds.), *Doctoral education and the faculty of the future* (pp. 53-64). Cornell University Press.
- Griffin, K. A., & Reddick, R. J. (2011). Surveillance and sacrifice: Gender differences in the mentoring patterns of Black professors at predominantly White research universities. *American Educational Research Journal*, 48(5), 1032–1057. <https://doi.org/10.3102/0002831211405025>
- Griffin, K. A. (2020). Rethinking mentoring: Integrating equity-minded practice in promoting access to and outcomes of developmental relationships. In A. Kezar and J. Posselt (Eds.), *Higher education administration for social justice and equity: Critical perspectives for leadership* (pp. 93-110). Routledge.
- Groth, D. P., & MacKie-Mason, J. K. (2010, February). Why an informatics degree? *Communications of the ACM*, 53(2), 26-28.
- Hodari, A. K., Ong, M., Ko, L. T., & Kachchaf, R. R. (2014). New enactments of mentoring and activism: U.S. women of color in computing education and careers. In *Proceedings of the Tenth Annual Conference on International Computing Education Research (ICER '14)*, 83–90. <https://doi.org/10.1145/2632320.2632357>

- Hug, S., & Jurow, A. S. (2013). Learning together or going it alone: How community contexts shape the identity development of minority women in computing. *Journal of Women and Minorities in Science and Engineering*, 19(4), 273–292. <https://doi.org/10.1615/JWomenMinorScienEng.2013005778>
- Jacobi, M. (1991). Mentoring and undergraduate academic success: A literature review. *Review of Educational Research*, 61(4), 505-532.
- Kincheloe, J. L. (2005). *Critical constructivism primer* (Vol. 2). Peter Lang.
- Kim, J-H. (2016). *Understanding narrative inquiry: The crafting and analysis of stories as research*. Sage.
- Layder, D. (1998). *Sociological practice: Linking theory and social research*. Sage.
- Lee, A. (2008). How are doctoral students supervised? Concepts of doctoral research supervision. *Studies in Higher Education*, 33(3), 267-281. <https://doi.org/10.1080/03075070802049202>
- Linder, C. (2019). Power-conscious and intersectional approaches to supporting student activists: Considerations for learning and development. *Journal of Diversity in Higher Education*, 12(1), 17–26. <https://doi.org/10.1037/dhe0000082>
- Maxwell, J. A. (2013). *Qualitative research design: An interactive approach* (3<sup>rd</sup> ed.). Sage.
- McCoy, D. L., Winkle-Wagner, R., & Luedke, C. L. (2015). Colorblind mentoring?: Examining White faculty mentoring of Students of Color. *The Journal of Diversity in Higher Education*, 8(4), 225-242. <https://doi.org/10.1037/a0038676>
- McGee, E. O. (2020). Interrogating structural racism in STEM higher education. *Educational Researcher*, 49(9), 633-644. <https://doi.org/10.3102/0013189X20972718>
- Mendoza, P. (2007). Academic capitalism and doctoral student socialization: A case study. *The Journal of Higher Education*, 78(1), 71–96. <https://doi.org/10.1080/00221546.2007.11778964>
- Miles, M. B., Huberman, A. M., & Saldaña, J. (2014). *Qualitative data analysis: A methods sourcebook*. Sage.
- National Academies of Science, Engineering, and Medicine. (2019). *The science of effective mentorship in STEMM*. The National Academies Press. <https://doi.org/10.17226/25568>.
- Newman, C. B. (2015). Rethinking race in student-faculty interactions and mentoring relationships with undergraduate African American engineering and computer science majors. *Journal of Women and Minorities in Science and Engineering*, 21(4), 323–346. <https://doi.org/10.1615/JWomenMinorScienEng.2015011064>

- Ogan, C. L., & Robinson, J. C. (2008). "The only person who cares": Misperceptions of mentoring among faculty and students in IT programs. *Women's Studies*, 37(3), 257–283. <https://doi.org/10.1080/00497870801917192>
- Ong, M., Wright, C., Espinosa, L., & Orfield, G. (2011). Inside the double bind: A synthesis of empirical research on undergraduate and graduate women of color in science, technology, engineering, and mathematics. *Harvard Educational Review*, 81(2), 172–209. <https://doi.org/10.17763/haer.81.2.t022245n7x4752v2>
- O'Meara, K., Kuvaeva, A., Nyunt, G., Waugaman, C., & Jackson, R. (2017). Asked more often: Gender differences in faculty workload in research universities and the work interactions that shape them. *American Educational Research Journal*, 54(6), 1154–1186. <https://doi.org/10.3102/0002831217716767>
- Packard, B. W., Marciano, V. N., Payne, J. M., Bledzki, L. A., & Woodard, C. T. (2014). Negotiating peer mentoring roles in undergraduate research lab settings. *Mentoring & Tutoring: Partnership in Learning*, 22(5), 433–445. <https://doi.org/10.1080/13611267.2014.983327>
- Polkinghorne, D. E. (1988). *Narrative knowing and the human sciences*. State University of New York Press.
- Pon-Barry, H., Packard, B. W.-L., & St. John, A. (2017). Expanding capacity and promoting inclusion in introductory computer science: A focus on near-peer mentor preparation and code review. *Computer Science Education*, 27(1), 54–77. <https://doi.org/10.1080/08993408.2017.1333270>
- Rorrer, A. S., Allen, J., & Zuo, H. (2018). A national study of undergraduate research experiences in computing: Implications for culturally relevant pedagogy. In *Proceedings of the 49<sup>th</sup> ACM SIGCSE Technical Symposium in Computer Science Education (SIGCSE '18)*, 604-609.
- Stephan, P. E. (2012). *How economics shapes science* (Vol. 1). Harvard University Press.
- Tashakkori, R., Wilkes, J. T., & Pekarek, E. G. (2005). A systemic mentoring model in computer science. *Proceedings of the 43rd Annual Southeast Regional Conference (ACM-SE 43)*, 1, 371-375. <https://doi.org/10.1145/1167350.1167453>
- Thiry, H., & Laursen, S. L. (2011). The role of student-advisor interactions in apprenticing undergraduate researchers into a scientific community of practice. *Journal of Science Education and Technology*, 20(6), 771–784. <https://doi.org/10.1007/s10956-010-9271-2>
- Thomas, D. A. (1993). Racial dynamics in cross-race developmental relationships. *Administrative Science Quarterly*, 169-194.

Tsai, J. Y., Kotys-Schwartz, D., Louie, B., Ferguson, V., & Berg, A. (2013). Am I a boss or a coach? Graduate students mentoring undergraduates in research. *120th ASEE Annual Conference & Exposition*, Article 6667.

Weigel, E. (2015). Modern graduate student mentors: Evidence-based best practices and special considerations for mentoring undergraduates in ecology and evolution. *Ideas in Ecology and Evolution*, 8. <https://doi.org/10.4033/iee.2015.8.3.c>

Wofford, A. M., & Blaney, J. M. (2021). (Re)Shaping the socialization of scientific labs: Understanding women's doctoral experiences in STEM lab rotations. *The Review of Higher Education*, 44(3), 357-386. <https://doi.org/10.1353/rhe.2021.0001>

## **CHAPTER 5:**

### **CONCLUDING REMARKS AND DIRECTIONS**

The final chapter of this dissertation offers a brief summary and synthesis of the three empirical studies presented in Chapters 2-4. Here, I discuss key commonalities and distinctions across the collective findings and provide insight for future scholarly endeavors related to these topics. While findings are discussed in greater detail within the individual papers (Chapters 2-4), this chapter reminds us where and why this stream of research originated, provides a concise illustration of some ways that the present findings can be joined in conversation, and serves as a summative catalyst for future streams of inquiry about equity in computing graduate school trajectories.

#### **Synthesizing the Scope of the Present Studies**

Across three distinct, yet related, studies in this dissertation, I explored the (in)equitable ways that mentoring interactions and psychosocial beliefs may shape graduate school trajectories in computing. My motivation to interrogate inequitable processes in graduate school pathways first stemmed from my personal and professional experiences (as discussed in Chapter 1). As I learned more about the unique predicament that computing fields face (e.g., growing student enrollments, structural and cultural challenges to the development of equity-minded policies and practices, market tensions with the tech industry that hinder faculty recruitment), I became invested in understanding how two significant areas that involve individuals' discretionary beliefs and actions (i.e., mentoring relationships and disciplinary psychosocial attributes) were shaped by the environments in collegiate computing departments. By generating new, equity-focused knowledge about how mentorship and psychosocial beliefs play a role in computing graduate school pathways, I aim to challenge how institutional actors and researchers think about

students' pathways to graduate school in computing and extend a more critical eye to the qualities of support and psychosocial beliefs that may foster or hinder such pathways.

The analyses and conclusions derived in this dissertation benefited greatly from the multiple conceptual approaches and methodologies that I employed across three studies. Given that the first study (Chapter 2) was completed before the succeeding studies (Chapters 3 and 4), I leveraged the findings and limitations of my initial work to design and execute two other studies that would extend the prior research with a more critical lens. The first study (Chapter 2) focuses on undergraduate students who aspired to earn a graduate degree in computing, investigating the extent to which their interactions within computing environments (e.g., introductory courses, computing departments) and their disciplinary psychosocial beliefs predicted their self-confidence in gaining admission to computing graduate school. While the first study examined disparities in self-confidence by gender and race/ethnicity, there remained significant potential to extend this work by incorporating a stronger focus on structural power in computing departments, further considerations of social identities, and particular types of mentoring relationships that may differentially characterize what “support” looks like within students' pathways to computing graduate school.

As such, I use approaches grounded in critical quantitative and critical constructivist epistemologies in Chapters 3 and 4, respectively. First, in Chapter 3, I examined inequities in the nature of mentoring support for graduate aspirants in computing departments as well the extent to which varying elements of graduate aspirants' mentoring relationships in computing departments shaped their disciplinary psychosocial development (i.e., computing self-efficacy, computing identity). Then, in Chapter 4, I engaged in a qualitative exploration of stage-ahead mentoring between graduate students and undergraduate students—a particular type of

mentoring relationship that graduate aspirants may have—to generate knowledge about equity-minded mentoring approaches from the perspective of graduate student mentors. Together, these foci make a significant contribution to empirical research on equity in mentoring relationships and graduate school trajectories within computing fields, and it is my hope that the findings discussed in this dissertation can inform generative conversations about revising policies and practices to meet the needs of historically minoritized students in computing.

### **Commonalities and Distinctions Across Key Findings**

While each study presented in this dissertation is unique, several elements of the findings speak to each other and inform central takeaways that can be expanded upon in the future. Here, I use a selection of key findings to briefly discuss (1) how inequity emerges in computing psychosocial development and (2) how inequity is reflected in mentoring relationships and support. By concentrating on these two areas of collegiate experiences, the findings and implications of this dissertation may shape the ways in which educational opportunity for computing graduate school is understood.

### **Inequity in Computing Psychosocial Development**

Psychosocial development in computing, and how disciplinary psychosocial beliefs play a role in computing graduate school pathways, was a primary focus of several research questions across the studies in this dissertation. Notably, in the quantitative studies (Chapters 2 and 3), I operationalized constructs of self-confidence for graduate school admission in computing, computing self-efficacy, and computing identity as outcomes of inferential analyses. Within the quantitative research questions that drove these analyses and interpretations, I was particularly concerned with the extent to which inequities existed in graduate aspirants' disciplinary psychosocial beliefs. In the findings of Chapters 2 and 3, I document significant disparities in

psychosocial beliefs associated with identity-based differences and also with how graduate aspirants engaged with particular departmental environments and mentoring interactions (e.g., support within coursework, structures of power among departmental mentors in computing). While the qualitative study presented in Chapter 4 did not centrally focus on disciplinary psychosocial beliefs as a research question, these attributes were a key part of stage-ahead mentors' narratives about how they approached mentoring conversations with undergraduates. In some ways, the covert way that psychosocial beliefs emerged in participants' stories helps illuminate how mentors may not always *name* psychosocial beliefs as such, but these attributes may be present as underlying ways that individuals make meaning of their experiences and trajectories in computing.

Independently, each study raises important findings about inequities in computing psychosocial beliefs. Yet, collectively, these findings speak to each other in even more important—and concerning—ways. For example, I quantitatively provide evidence to note the depreciation of women graduate aspirants' self-confidence in computing graduate school admission, relative to their peers who are men (Chapter 2). I also document the ways in which the gender gaps in computing identity become wider over time among graduate aspirants in computing who had a departmental mentor, with women's sense of computing identity remaining significantly lower than that of men after controlling for variables related to their mentoring relationships (Chapter 3). For women interested in pursuing computing graduate school, these results suggest that the culture of their undergraduate computing environments or their mentoring relationships in computing departments may play a negative role in the ways that they consider themselves as “computing people” who may be able to successfully make the transition to graduate school. Further, by qualitatively exploring stage-ahead mentorship between

graduate and undergraduate students, I was able to discuss *how* gender identity operated as a central consideration to the cultivation and provision of mentorship for several participants, especially those who identified as non-binary or as cisgender women—gender identities that are often minoritized by policies, practices, and organizational cultures in computing fields.

As a second example of how findings work in concert, the present studies collectively support my assertion that disciplinary psychosocial beliefs are key mechanisms that may bolster or burden the translation of graduate school aspirations to matriculation decisions in computing. Indeed, given that both quantitative studies used samples of students who held aspirations for graduate school, the prominent inequities documented in self-confidence for computing graduate admission, computing self-efficacy, and computing identity substantiate the claim that exploring graduate aspirations *alone*—as has been done in a wealth of empirical work across all fields—is not enough to ensure equitable support for matriculation to computing graduate school. There are many structures, social cues, and salient identities that continue to shape students’ decision-making after they indicate an interest in graduate school. Looking to the narratives of current computing graduate students who engaged as mentors to undergraduates (Chapter 4), doctoral students revealed drawing on earlier experiences related to identity and inclusion in computing spaces and other lived experiences to provide guidance to their mentees. Psychosocial beliefs begin forming far before graduate school, evidenced not only by these narratives but also by the significant association that introductory course psychosocial traits had with students’ later beliefs (i.e., quantitative outcomes); thus, the implications discussed in Chapters 2 and 3 advance practical considerations for college administrators as well as K-12 leaders and educators.

## **Inequity in Mentoring Relationships and Support**

Just as the lessons learned about psychosocial inequities advance the notion that simply having graduate aspirations is not enough to ensure that matriculation goals are equitably realized, the present findings also support the fact that having a mentor is not enough to ensure equity-minded interactions and beneficial outcomes of mentoring relationships in computing graduate school pathways. Mentoring support and relationships were examined in varying capacities across these three studies, with general mentoring support during the introductory course being a construct of interest in Chapter 2, the ways in which mentoring relationships in computing departments may be shaped by structural and cultural power being a key focus of Chapter 3, and a nuanced exploration of identity, organizational context, and stage-ahead mentoring between graduate and undergraduate students characterizing the purpose of Chapter 4.

The multiple methods and foci across studies allowed me to generate a more robust understanding about the ways that mentoring experiences shape computing graduate school trajectories. Across the findings in this dissertation, it became clear that context underscores the quality of mentees' experiences. For example, in Chapters 2 and 3, general mentoring support during introductory computing courses significantly shaped graduate aspirants' self-confidence for computing graduate admission and computing self-efficacy beliefs; however, this relationship emerged in opposite ways. In Chapter 2, intro course mentoring support played a positive role in cultivating self-confidence for computing graduate admission, but only when compounded with supportive departmental environments (during the intro course) and higher levels of computing self-efficacy (two years after the intro course). Given this association between intro course mentoring support and computing self-efficacy in Chapter 2, I was surprised to find that such mentoring support held a negative relationship with computing self-efficacy in Chapter 3.

Together, these findings suggest that supportive departmental environments are a crucial link—and one that may not be established by the primary departmental mentor alone.

Additionally, these studies show that mentoring interactions (and outcomes) may often depend on how power is structured within collegiate computing. In several ways, findings (especially in Chapters 3 and 4) discuss how the quality of mentoring is situated within broader social structures and imbalanced systems of power, which are dynamics that may play an especially large role in characterizing mentoring relationships for students with historically minoritized identities in computing. In Chapter 4, stage-ahead mentors prioritized empowerment and transparency in their mentoring approaches; sometimes, these tactics were related to their precarious positions as doctoral students or having shared lived experiences with mentees in oppressive environments. The stories that graduate students shared about their mentoring approaches may illuminate a nuanced part of psychological and emotional mentoring support, which, as revealed in Chapter 3, was provided more often by graduate students (and other advanced peers) as opposed to faculty members in computing. While the findings in Chapter 3 document that computing faculty members do not provide as much psychological and emotional support to graduate aspirants, this is not to say that faculty *should* not provide empowering support. In fact, several stage-ahead mentors in Chapter 4 noted drawing inspiration from seeing their faculty advisor cultivate empowering mentoring relationships; yet, if faculty are not mindful of their mentoring approaches, graduate students may observe and reproduce harmful mentoring dynamics.

### **Primary Contributions and Avenues for Future Inquiry**

I entered this dissertation work plagued by questions and concerns about equity in students' pathways to computing graduate school and aiming to contribute to the conversation

about how to support students—and especially those with historically minoritized identities—to pursue a graduate degree in computing. The task of supporting students in their graduate school aspirations has long been a concern of many universities and departments, in computing fields and beyond. Yet, the student-level nature of these concerns has often resulted in findings and implications that disproportionately focus on student-level actions, rather than understanding students’ pathways in larger departmental and institutional structures. The studies included this dissertation collectively reflect the empirical transition—as well as my own scholarly transition—from framing that focuses on an individual level (with organizational context) to framing that views the individual and organization working in tandem, with a more explicit focus on how power and culture operate in mentoring relationships within computing. This progression of framing marks one of the larger contributions afforded in a three-article dissertation and a valuable (re)framing that future scholars may consider in their own work. Without explicitly considering the ways organizational power and context influence mentoring relationships, psychosocial beliefs, and graduate school trajectories in computing, any changes to policy and practice will fall short of their systemic potential.

As discussed in the synthesis of findings above, two of the larger contributions from these studies lie in the assertion that (1) studies on computing graduate school pathways must move beyond considerations of aspirations in order to consider the inequities and structural barriers that may disrupt the translation of aspirations to matriculation, and (2) studies on mentoring relationships in computing graduate pathways must carefully attend to the influence of multiple mentors in computing departments, and how varying mentors may face different affordances and constraints to providing equity-minded guidance based on their positional power within the institution. In taking a three-article approach to this dissertation, I was presented with

the opportunity to delve into several nuanced areas of research concerning (in)equity, mentorship, psychosocial beliefs, and graduate school pathways in computing. Yet, as noted within each article, there remains significant potential for future researchers to continue extending the empirical conversation about these topics.

Among the many avenues that future research on equity in computing graduate school pathways could occupy, several topics are particularly pressing. First, research on computing graduate school trajectories would benefit from a greater understanding of why students do *not* fulfill their stated aspirations of attending graduate school. While making the decision to pursue another path is not inherently a negative one, former graduate school aspirants may hold crucial insight regarding institutional barriers to graduate school matriculation. Second, the studies in this dissertation used data about mentoring experiences from one timepoint, and it is crucial that scholars consider ways to collect longitudinal mentoring data. Just as students' academic pathways take varying turns throughout college, so do their relationships with mentors. Finally, it is necessary for forthcoming research to consider using critical organizational lenses to understand the institutional context, departmental culture, and relational dynamics that shape students' decision-making about graduate school and their mentoring experiences—among both graduate students who are serving as mentors and undergraduates who are receiving mentorship.

As future research evolves, it is my hope that scholars and practitioners can blend their learned and lived knowledge to disrupt the inequitable processes and structures that have maintained disparities in computing graduate school opportunities and experiences. Just as technology itself can benefit from disruptions, with human intervention to reset and reconfigure the structures and operation of such technology, computing departments should consider how

disruption, with intervention from research and practice, can underscore an equity-minded reset for graduate school pathways.