Computing Undergraduate Students’ Participation in Internships

Experiences, Preparation, and Barriers

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Abstract

Internships provide students an opportunity to gain authentic disciplinary experiences, understand professional expectations, evaluate self-interests, and secure future employment. However, little is known about students' participation in internships within the computing discipline and the role that internships play in students' professional development. My completed and proposed work aims to fill this gap by systematically assessing computing undergraduate students' participation in internships. I will present three of our prior studies that highlight (1) the importance of internships in computing through the lens of student experiences, (2) an empirical evaluation of students' participation in internships underscoring who participates, who does not participate, and how participation gets influenced by students' preparation processes or other situational barriers, and (3) a pedagogical intervention that we can include in our curriculum to prepare students for securing internships. Data used in these studies were collected using surveys and interviews from 1207 undergraduate computing students enrolled across three universities. My proposed research will develop personas using data from these studies highlighting the differences between students who successfully secure internships and those who do not. I also propose a fourth study to retrospectively evaluate the efficacy of our intervention in aiding students to secure real-world internships. My work contributes to computing education literature empirical knowledge on computing students' participation in internships. This knowledge has the potential to increase students' competitiveness for employment outcomes as well as align our degree programs to student goals.

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Part I: Overview

1. Introduction

When I joined the doctoral program, I was interested in understanding how computing students' form professional identities in computing. For exploring this phenomenon, my initial work identified how computing education researchers conceptualize or operationalize identity [82], how students describe their professional identities [74], the factors and avenues that influence their identity formation processes [79], and the chronology of this process [79] in the context of computing undergraduate programs. This research provided insight into the crucial role played by informal and non-formal learning environments such as internships, personal projects, student organizations, and hackathons on students' identity formation. Previously, most researchers working in this area had focused on understanding identity formation [13, 93, 94, 121–123, 139] by assessing students' involvement in academic degree programs. However, based on findings from my first study [79], I decided to explore computing students' participation in internships given their role in professional identity formation and their impact on students' professional careers.

An internship is a professional learning experience that provides students an experiential learning opportunity to gain practical skills related to their field of study or career choice [69, 137, 138] for a limited period of time in a low stakes environment. It allows students to explore their chosen discipline, acquire new skills, and gain authentic experience through interactions and engagement with broader communities of practice and become members of the community [138]. For employers, internships offer the chance to bring new ideas into their workplace, nurture talent, and possibly identify future full-time employees [143].

Internships evolved from apprenticeships and modern-day internships were first offered in 1889 in the context of medical education [153]. Internships have been studied extensively in several domains such as nursing [32], psychology [145], management [33], business [60], education [140], etc. Within computing, in the early 1970's, internships provided students hands-on experiences to work with a computer or allowed them to gain insights into industry expectations [159]. Universities facilitated internship programs coordinating with industry partners [142]. The importance of internships in computing have been documented and discussed since as early as 1974 by Goddard [53] who suggested that internships prepare students for industry jobs and recommended administrators to integrate internships more formally in computer science (CS) curriculums. For the integration of internships in formal education, Jones [71] described in 1975 a university program that required students to participate in co-op or internships for credit "after the data structures course". However, there weren't many employers who offered such opportunities and hence Archibald and Katzper [4] recommended that industry stakeholders should offer more paid internships for preparing computing students for their jobs. More recent work on internships in computing have focused on exploring the value students get from participating in internships [106] or developing academic scaffolded programs that provide students with value that professionals may otherwise receive from internships [50, 103]. *While most of this work is focused on understanding the value of internships and developing interventions that foster these values in the context of formal academic programs, we do not know much about who is participating in the real-world internships in computing.*

My completed and proposed work aims to fill this gap by systematically assessing computing undergraduate students' participation in internships. Note that securing a real-world intern position related to computing in the tech or other industries is competitive, and the recruitment process broadly subsumes stressful and infamous technical interviews [10, 11, 59]. The central research question I aim to answer through my doctoral work is “***How do computing undergraduate students secure and participate in internships? What barriers prohibit them from participating in internships?*”.** In this proposal, I present three studies that I have already published in five peer-reviewed conference papers and propose a fourth study. The data for these studies was gathered through surveys and interviews from 1207 undergraduate computing students at three universities. Overall, **my work contributes to computing education literature empirical knowledge on computing students' participation in internships.** This knowledge has the potential to improve students’ employment outcomes as well as align our degree programs to student goals.

Study 1 & 2: Understanding Student Preparation and Participation in Internships. The first two studies and their findings (1) emphasize the significance of internships in computing based on student experiences, and (2) provide an empirical assessment of students’ participation in internships underscoring who participates, who does not participate, and how participation gets influenced by students’ preparation processes or other situational barriers. Based on these studies, we found that a majority of our students are not participating in internships due to cognitive, psychosocial, and socio-economic constraints. This led to several questions: *How do we get these students to participate in internships? How do we improve our programs so students can participate more? How do we improve our programs so that those who can’t participate, can acquire the skills needed to secure a full-time job or have a successful professional career?* The latter question reinforces John Dewey’s ideas who argued that in order for education to be most effective, content must be presented in a way that allows a student to relate the information to prior experiences, thus deepening the connection with this new knowledge [45, 132, 157]. Are we as educators doing our part to create ample prior experiences so that students have a smooth transition to an industry role without necessarily having internship experiences?

Study 3: Intervention & Evaluation. For my third study, I focused on answering these questions by preparing students to secure jobs in industry and make the transition to industry as seamless as possible by improving our curriculum. **Study 3 describes and evaluates a pedagogical intervention for our curriculum called *Hire Thy Gator Technical Interview Exercises* that can prepare students for securing internships.**

Proposed Work: Further Analysis & Study 4. To complement the analysis from the three studies, **I propose to develop rich descriptive personas** using data from these studies **highlighting the differences between students who successfully secure internships and those who do not**. This work will answer the following research question (PRQ1.): “***How are computing undergraduate students who successfully secure internships different from those who have not interned?***”. Additionally, I propose a fourth study to retrospectively evaluate the efficacy of our intervention in aiding students to secure real-world internships. This study will answer the following research question (PRQ2.): “***How effective are Hire Thy Gator Technical Interview Exercises in preparing computing undergraduate students for securing industry internships?***”.

Organization of Proposal. Since I have completed two-thirds of the research prior to proposing, my advisor and I decided to organize this proposal as a compilation of my published work. This work has focused on understanding the factors that contribute to successful and unsuccessful pursuits to secure internships for undergraduate computing students and designing and evaluating an intervention to support all students in their internship preparation within their degree coursework. As such, each study is presented as a chapter. At the beginning of each study chapter, I briefly describe the study, research questions, cite the publications that resulted from that study, and highlight the papers that I have combined to create the chapter’s content. Thus, each study chapter is organized as a conference publication with an introduction, background/related work, methods, results/findings, discussion, and conclusions. I then describe the resulting research questions that guide subsequent work. Thus, I have reused the text published in these papers as well as written new text that synthesizes multiple papers together to ensure that chapters read coherently. Given this presentation style, we have decided not to include lengthy introduction and related work chapters as each study chapter identifies the motivation for the work, problems of practice and research they address, and reference different aspects of the computing education literature.

This document is organized into three parts. *Part I: Overview* includes an introduction (this chapter) and theoretical grounding that describe the theories that guided our research studies. *Part 2: Completed Work* includes three chapters that present Studies 1-3 we conducted including the prior work for each study, methodology, analysis, and findings. *Part 3: Proposed Work* describes the work I will complete for this dissertation that includes additional analysis of data from Study 3 to develop personas and a description for Study 4, Retrospective Evaluation of Hire thy Gator Intervention. Last, I will elucidate the expected contributions from my doctoral work.

2. Theoretical Grounding

Our exploration into the characteristics of individuals who have been and have not been able to obtain internships is rooted in agency as described by Bandura's Social Cognitive Theory [6], Lent et al.'s Social Cognitive Career Theory [23, 89] which builds on Bandura's theory, and James Marcia's theory of identity development [96]. These theories identify the characteristics of agentic behavior and how they shape an individual's ability to set and pursue goals and achieve their career aspirations. These theories informed our studies' research questions, data collection instruments, and qualitative data analysis process which are described in Chapter 5.

2.1 Bandura's Social Cognitive Theory

Self-efficacy is the belief that one has about their capacity for specific achievements, given domain-specific obstacles [5, 7]. Self-efficacy beliefs determine how people feel, think, motivate themselves and behave. Contrary to self-efficacy which expresses an individual's perception, agency illustrates an individual's actual ability to deal with a complex task. Bandura's Social Cognitive Theory identifies the characteristics of agentic behavior and how they shape an individual's ability to set and pursue goals. Bandura suggests that human agency has four core properties: intentionality, forethought, self-reactiveness, and self-reflectiveness [8]. *Intentionality* is an individual's intentional planning and strategies for achieving specific outcomes. *Forethought* includes temporal extension of agency and lets an individual visualize futures through cognitive representations that guide prospective actions. Agency is not limited to planning and forethinking but also includes self-reactiveness. *Self-reactiveness* allows an agent to "construct appropriate courses of action" and "regulate" behaviors [8]. Last, *self-reflectiveness* lets an individual examine their functioning meta-cognitively and make corrections accordingly for future actions [8]. Bandura states that people who develop their competencies and self-regulatory skills are more successful in realizing desired futures, than those with less developed agentic resources. We use this theory to interpret our qualitative and quantitative data on students' internship seeking behavior.

We believe that securing an internship position (a desired future outcome) requires high self-efficacy and agency from a student. This agency further leads to the cognitive development of skills that are required to secure an internship. Demonstration of an individual's agency or agentic properties can be identified through action proxies including students' behavior of intentionally applying for internship positions, preparation for technical interviews, or students' agency to develop technical and professional skills that are sought by employers. Thus, students who are not securing internships may lack forethought, intentionality, or other agentic resources or may not have access to social structures that foster the development of agency.

2.2 Social Cognitive Career Theory

Social Cognitive Career Theory (SCCT) models and explains the three primary mechanisms that promote career exploration and attainment: self-efficacy, outcome expectations, and performance goals [89]. In particular, an individual's interest in career-relevant activities is directly related to their self-efficacy and outcome expectations. SCCT posits that in order for an individual to form a sense of efficacy and to acquire outcome expectations about their engagement in career-relevant activities, they need continued exposure, practice, and feedback on their performance in these activities. Such extended engagement enables individuals to refine their skills and helps them to develop personal performance standards and goals [89]. SCCT further suggests that for interests to develop, individuals must be exposed to the types of "direct, vicarious, and persuasive" experiences that can give rise to and reinforce efficacy beliefs and positive outcome expectations [89].

Thus, people are likely to form a lasting interest in activities when they view themselves as competent and when they expect that they will produce valued outcomes. Without such experiences, regardless of their level of skills, talent, and interest, SCCT suggests that individuals do not have the opportunity to form strong self-efficacy and positive outcome beliefs. We used this theory to guide the development of our data collection instruments, the survey and the interview scripts. Specifically, we gauge if and how students are exposed to "direct, vicarious, and persuasive" experiences during the 4+ years in their degree program that foster professional growth and improve their employability.

As one might expect, individuals' interests in activities are unlikely to develop when individuals doubt their competence and expect negative outcomes. As a result, individuals who do not have the opportunity to reinforce their skills, experience impediments during career exploration and attainment. Moreover, as individuals engage in the process of career exploration and skill development, they also encounter other obstacles e.g., financial, cultural, systemic, or have varying levels of support from influential others [89]. Therefore, in our data collection instruments we specifically added questions to understand the obstacles student face during employment process and will shed light on these barriers as a part of my completed (described in Chapter 4) and proposed (described in Chapter 6) work. Thus, personal agency is necessary to help individuals form performance goals and provide motivation to overcome common obstacles and barriers inherent in skill development, career exploration, and career attainment. As a part of the data analysis of my proposed work (described in Chapter 6), I will specifically look for how agency plays a role in students' ability to secure internships highlighting the avenues, processes, and stakeholders which foster and impede students' agency.

2.3 James Marcia's theory of identity development

James Marcia's theory of identity development operationalizes stages of identity development [96] and suggests that professional identity forms during ages 17-23 based on a person's active or passive exploration and commitment to their chosen profession or discipline. The theory identifies four statuses to characterize individuals' identity development: (1) *identity diffusion*, when an individual is neither exploring nor committed to a career choice; (2) *identity foreclosure*, when an individual has not explored career options but is committed to a career due to influence of an external agent; (3) *identity moratorium*, when an individual is exploring career options but is not committed to a career choice; and (4) *identity achievement*, when an individual has explored career options and is committed to an identity after the exploration process. The theory proposes that identity develops during active exploration highlighted by the moratorium and achievement statuses. Our first study (Chapter 3) focused on understanding professional identity formation [74, 75, 79] and we were interested in determining the unexplored relationship between identity formation and internship participation in computing in our second study (Chapter 4). To analyze this relationship quantitatively, we used the validated Extended Objective Measure of Ego Identity Status (EOM-EIS) instrument [12] which is based on James Marcia's theory of identity development [96] in Study 2 (Chapter 4). The EOM-EIS instrument provides measures to quantitatively represent identity statuses [12].

The three theories described in this section provide cognitive and situated perspectives on learning and collectively influenced our study design, research questions and instruments, and data analysis. When analyzing data, I will focus on understanding the role of task or domain-specific constructs from these theories (e.g. self-efficacy) as well as more stable and broader constructs (e.g., identity) on students' participation in internships.

Part II: Completed Work

3. Study 1: Why are internships important?

I conducted my first study as a student in the Master's program under the supervision of my advisor, Dr. Christina Gardner-McCune. This exploratory study was associated with the CS Identity project and focused on understanding computing students' professional identity formation at a single institution, the University of Florida. We designed this study in Fall 2015 and collected data using mixed methods (a survey and interviews) in Spring 2016. We analyzed the data collected from this study from 2017 and our results and findings were published in the following conference proceedings under the research papers category between 2017-2019 during my time in the HCC Ph.D. program:

1. *Papers*
    a. *Understanding Professional Identities and Goals of Computer Science Undergraduate Student* at the ACM SIGCSE TS 2018 Conference (Technical Symposium on Computer Science Education) [74].
    b. *Considerations for Switching: Exploring Factors behind CS Students' Desire to Leave a CS Major* at the ACM ITiCSE 2018 Conference (Innovation and Technology in Computer Science Education) [76].
    c. ***Understanding CS Undergraduate Students' Professional Development through the Lens of Internship Experiences* at the ACM SIGCSE TS 2019 Conference** [77].
    d. *Understanding CS Undergraduate Students' Professional Identity through the lens of their Professional Development* at the ACM ITiCSE 2019 Conference [79].
2. Posters
    a. Understanding How Computer Science Undergraduate Students are Developing their Professional Identities at the ACM SIGCSE TS 2018 Conference [75].
    b. **Deconstructing Successful and Unsuccessful Computer Science Undergraduate Interns at the ACM SIGCSE TS 2019 Conference** [73].
    c. Understanding Aspiring UX Professionals' Professional Development at the User Experience Professionals Association (UXPA) 2019 Conference [78].

I was the lead author on all of the above papers and Dr. Gardner-McCune was the supervisor and co-author. The publications that are bolded are described in this chapter.

Motivation & Background. In our first paper [74], we found that a majority of computing undergraduate students (82% of the 109 students we surveyed) identify themselves professionally with computing areas or job roles such as Software Engineers, Data Scientists, Cybersecurity professionals, etc. Additionally, a majority of students (65%) identified their professional goal as to secure a job in industry after graduation. One avenue that helps students in securing jobs and developing as a professional is industry internships [69, 138]. While internships have been explored in other domains [15, 32, 33, 60, 65, 140, 145], there wasn't much research on students' participation in internships in computing. Hence, we investigated how internships are valuable for students in computing [77].

In this section, I will elaborate on Paper 3: *Understanding CS Undergraduate Students' Professional Development through the Lens of Internship Experiences*, to demonstrate the value students receive when participating in real-world internships. In addition, I will shed light on our preliminary investigation of students' participation in internships through the findings from my poster, *Deconstructing Successful and Unsuccessful Computer Science Undergraduate Interns*, which was presented at the ACM SIGCSE TS 2019 Conference as a part of the Student Research Competition track [73]. This investigation motivated us to conduct Study 2 which will be discussed in the next chapter (see Chapter 4).

3.1 Introduction

The US Bureau of Labor Statistics projected that by 2020 there will be 1.4 million computer science (CS) related jobs available and 400,000 CS graduates with the skills to apply for those jobs [163]. In addition, CS jobs are projected to grow at 13% over the next decade [66]. While academic institutions are working to keep up with surging enrollments to educate students to address the increasing industry demand [25], 26% of the recent CS major graduates are underemployed in the United States according to a 2018 report by the Federal Reserve Bank of New York [164]. This suggests that current CS graduates may be underprepared to secure computing jobs, thus exacerbating the current challenge the US educational system is facing in attracting and preparing enough CS students to satisfy this demand. As academic institutions, our role is to create pathways for career preparation through our degree programs to help students gain entry into various computing communities of practice (CoP) [152] and to make their transition from college to the industry as effective as possible. One way that students access these CoPs is through internships. Internships allow students an opportunity to undergo experiential learning thereby enhancing an undergraduate's intellectual, personal, and ethical growth [51].

While internships have been extensively studied in other disciplines [15, 32, 33, 60, 65, 140, 145], research on internships in computing is limited. Therefore, in the study presented in this paper, we focus on understanding the impact that computing internships have on students' career goals. In addition, we investigate students' perceptions of our curricula's effectiveness for preparing them for jobs in the industry and the strategies students incorporate for professional success. We present a thematic analysis of open-ended survey responses of 40 CS undergraduate students in the United States who participated in an internship. We found four themes on the impact of internships on CS students. Internships: (1) *strengthened students' commitment to their CS degrees and careers*; (2) *encouraged exploration of CS careers and industries*; (3) *promoted personal/professional growth*; and (4) *developed awareness of professional expectations*. We further analyzed students' perception of the curriculum's effectiveness in preparing them for CS careers and found that students had mixed opinions on the effectiveness of computing curricula in preparing them for industry. We also observed that students were strategically working outside of their coursework to improve their technical skills and secure future employment. Our work provides insight into CS students' professional development process. This knowledge has the potential to reduce the gaps between academia and industry, thereby increasing CS students' competitiveness in the workforce and retaining them in computing degree programs.

3.2 Theoretical Background: Situated Learning, Communities of Practice

In the context of undergraduate degree programs, internships are one avenue for students to initially participate in computing communities of practice (CoP). Lave and Wenger's Situated Learning theory describes how individuals acquire professional skills through co-construction of knowledge when interacting in a social context, apprenticeship, or CoP [87]. Wenger states that "*Communities of practice are formed by people who engage in a process of collective learning in a shared domain of human endeavor: a tribe learning to survive,[...] a clique of pupils defining their identity in the school [...]. In a nutshell: Communities of practice are groups of people who* *share a concern or a passion for something they do and learn how to do it better as they interact regularly*" [17]. Wenger's CoP research extends research on apprenticeship [152], Situated Learning theory [87], and legitimate peripheral participation (LPP) [152]. The learning that takes place in these CoPs is situated in a specific context or environment and involves more than the acquisition of skills and knowledge. Learning in a CoP involves a change in a person's identity as well as in how a person understands themselves in relation to a particular disciplinary practice (e.g., computer science).

The theory of legitimate peripheral participation describes how members of CoP start off on the periphery of the community as a newcomer. As newcomers gradually gain understanding and mastery of key skills and practices valued by the community, they become more central to the functioning of the community and are eventually recognized as old timers within the community [152]. Throughout this process of participation in the community, members' identities are reconstructed and transformed as they seek to become full practitioners within the community. While there are official pathways to earning credentials to become part of most professional CoPs, participation in the community is essential for recognition, acceptance, and membership within the community [152].

In the context of computing CoP, internships offer students who are newcomers to the computing industry a way to become members of a community by allowing them to participate in simple tasks that further the goals of the community/organization. Through these peripheral activities, computing students become acquainted with the tasks, vocabulary, and organizing principles of the computing community and its practitioners. This theory was used to design our study and understand the impact the internships have on students' professional identities and career development.

3.3 Related Work

3.3.1 Role of internships in future employment

Internships have become an integral part of employers' recruitment process as they provide them the ability to evaluate potential candidates over an extended period of time in a working environment [109, 137]. Studies have shown that pursuing an internship is positively correlated with an improved chance of getting a full-time job offer and a higher starting salary [109]. A 2017 National Association of Colleges and Employers (NACE) survey reported a staggering 91% of employers considered candidate experience when making hiring decisions and half of the employers sought new graduates to be hired from an internship or a co-op program [165]. In addition, NACE also surveyed 44,000 students in 2014 and found that 52.1% of students with an internship or co-op who applied for jobs received at least one offer of a full-time position compared with 38.6% of applicants without the internship or co-op—a difference of 13.5% [109]. Thus, it is evident that internships are playing a key role in preparing students for their professional careers and helping them to obtain full-time positions. However, little is empirically known about the impact these internships have on computing students and how effective are our programs in preparing students to secure and excel in industry internships.

3.3.2 Existing research in CS undergraduate professional development

Most research in professional development for CS undergraduate students has focused on the professional development of students through participation in capstone courses [116, 118] or project-based courses [43], or experience in internship programs developed through industry-academia partnerships [50]. This research includes

Fryling et al.'s study [50] on the introduction of an internship program for upperclassmen at Siena College. They found that a department-scaffolded internship program had a positive impact on CS student's retention. In addition, Parker [118] did a study to understand the influence of a software engineering capstone course at an R1 research institution in the US on professional identity formation. He categorized students' responses and artifacts using the "Becoming an Engineer" framework and found that students identified themselves with CS professions and explored career options through the capstone project. Parker also did a study on understanding professional development through capstone projects and found that students' affective responses during their capstone projects provide an indication of their engagement and investment in the CS projects [117]. Tomer and Mishra [150] interviewed students in a prominent university in India and found that CS students described a noticeable gap between their academic training and their internship experience which led them to have mixed satisfaction with their CS degree program and the program's role in preparing them for their future careers. Our work however focuses on a different context, real world industry internships in the United States and we plan to investigate the impact of internships on computing undergraduate students.

3.4 Methods

3.4.1 Study design

We designed a cross-sectional survey-based study focused on understanding the impact that professional internships have on: CS students' career goals, students' perceptions of the gaps between academia and industry, and students' strategies for professional success. 97 students enrolled at a R1 public university, University of Florida participated and completed a survey in Spring 2016. The university had a population of 1519 undergraduate CS majors in 2016. The CS undergraduate degree program offered at the University of Florida allows students to major in CS or Computer Engineering (CE). The students can choose a major when they start college but can change it at any time. For this paper, we report on the data of 40 CS undergraduate students who participated in an internship. In this paper, we focused on exploring the following research questions:

RQ1. How do professional internships impact CS undergraduate students?

RQ2. What lessons can we learn from CS undergraduate students' professional experiences that can strengthen our academic curriculum?

RQ3. What lessons can students learn from CS undergraduate students' professional experiences that can aid to their professional success?

3.4.2 Participants recruitment

Students were recruited from the University of Florida's CS1, data structures, software engineering, senior design, Human-Computer Interaction courses and several CS technical electives. The survey participants were given extra credit for participating in this study - not more than 1% towards their final grade based on pre-approval by the respective course instructors. Additionally, students were given an alternate assignment worth similar credit if they opted out of the study. The second author (Dr. Gardner-McCune) was one of the instructors who offered extra credit in the software engineering course, but the data was collected by the first author (myself) and not shown to the second author until after grades were submitted for the course.

3.4.3 Participants

The age range of the participants was 18 to 23 based on the enrolled CS undergraduate population at the University of Florida. The details of the survey respondents are as follows: 148 students responded to our survey; 102 students completed more than 94% of the survey. Out of the 102 students, 5 students did not major or minor in CS or CE. Thus, we were left with 97 CS/CE undergraduate students. Of these 97 CS students, 41.2% participated in an internship (n=40). Further, we found that an equal proportion of males and females in our survey sample participated in internships: 40.9% of 22 females (n=9) and 40.5% of 74 males (n=30). The students who interned included 1 freshman (6.3% of 15), 57.1% of 14 sophomores (n=8), 44.8% of 29 juniors (n=13), 42.4% of 33 seniors(n=14), and 80.0% of 5 super-seniors (n=4). For this paper, we exclude the data for students who did not have prior internship experience as we want to explore what students get out of internships. Thus, we report data on 40 CS undergraduates (41.24% of 97) who completed more than 94% of the survey and had an internship experience. These students consist of 30 males and 9 females. One student did not report gender. The students who interned included 1 freshman, 8 sophomores, 13 juniors, 14 seniors and 4 super-seniors (4+ years in the program).

3.4.4 Data collection

We gained consent from the Institutional Review Board at the University of Florida and used Qualtrics to administer the survey. The participants were asked to complete a consent form prior to the survey. The survey consisted of 3 demographic-related, 36 multiple choice, and 16 open-ended questions and was completed on average within 32 minutes. For this paper, we focus on 6 open-ended questions that are relevant to answering our research questions (see Table 1). We also use three demographic questions on gender, major, and academic standing and one multiple choice question on whether they participated in an internship.

Table 1. Survey questions analyzed for answering research questions (as reported in Kapoor & Gardner-McCune, SIGCSE 19)

Research Question	Survey Questions
RQ1. How do professional internships impact CS undergraduate students?	Describe the impact of internship experiences on your career goals and interests.
RQ2. What lessons can we learn from CS undergraduate students' professional experiences that can strengthen our academic curriculum?	* How well has the CS curriculum here at the university prepared you for industry and/or research professional experiences? * Can you think of a course whose use/application was way different in the industry than as taught here at the university? * Describe your experience in the CS/CE degree program? Reflect on the quality of your academic experience. * Please provide additional comments or suggestions for improving the degree program and experience at the university.
RQ3. What lessons can students learn from CS undergraduate students' professional experiences that can aid to their professional success?	Reflecting on your degree experience, what advice would you give to students enrolled in this program to improve their experience in the program and their professional success?

3.4.5 Data analysis

We analyzed student responses to six open-ended questions using inductive thematic analysis in Microsoft Excel. We were following a grounded theory process of inductive coding [39]. We started with the raw data and created codes inductively using words from participants' responses. The first author created primary codes which were then clustered to form categories, and these categories formed the basis of our codebook (see Table 2). We coded 129 student responses into 150 primary codes, which were clustered to form 78 categories. We then combined these categories into themes. 11 themes emerged to answer our three research questions: 4 for RQ1, 4 for RQ2, and 3 for RQ3.

Table 2. Example of Inductive Content and Thematic Analysis (as reported in Kapoor & Gardner-McCune, SIGCSE 19)

Survey Question: Have you participated in any internships? If yes, how did it affect your career goals and interests?			
Raw Data	It made me *like my career* even more.	It made me *not want to change my CS major* anymore.	Helped me to *decide on CEN* [Computer Engineering].
Primary Code	Like a CS career	Not change a CS major	Choosing Computer Engineering
Category	Strengthened to pursue a CS career	Strengthened to pursue a CS major	
Theme	Strengthened students' commitment to CS degrees and careers		

To verify the reliability of the first author's coding scheme, the second author performed the inter-rater reliability at the theme level on 36% of the dataset chosen at random. The Cohen's Kappa was an average of 0.72 for the coding scheme which qualifies as a substantial agreement [86]. The authors discussed the themes in which there was a disagreement until a consensus was reached about the theme accuracy and reliability. Table 2 highlights an example of our inductive content and thematic analysis [39]. This was followed by a frequency analysis of responses within each theme. We counted unique participants when computing these frequencies, to avoid counting multiple responses from the same participant within any theme. There were some participants whose responses belonged to more than one theme and thus the percentages don't add up to 100%.

3.5 Findings/Results

3.5.1 Impact of professional internships

We analyzed student responses to an open-ended survey question: *Have you participated in any internships? If yes, how did it affect your career goals and interests?* Thirty-four students who interned responded to this question. Four themes emerged from our data analysis on the impact of professional internships on CS undergraduate students' career goals (RQ1). These themes and their respective frequencies are shown in Table 3.

Table 3. Themes for Impact of Internships on Career Goals (as reported in Kapoor & Gardner-McCune, SIGCSE 19)

Themes for impact of internships on career goals	**n (N = 34)**	**%**
strengthening students' commitment to CS degrees and careers	14	41.1%
encouraging exploration of CS careers & industries	12	35.3%
promoting personal/professional growth	6	17.6%
developed awareness of professional expectations	5	14.7%

Strengthening students' commitment to CS. We found that internships played a crucial role in strengthening CS students' commitment to pursue a CS major or CS careers. 41% of 34 students (n=14) mentioned that the internship had a positive impact on their career goals: strengthened their career goals, instilled in them interest in CS, or made them determined to pursue a CS major. The two most prominent categories in this theme included: *strengthened their commitment to pursue a CS career* and *strengthened their commitment to pursue a computing major*. All three students who belonged to "strengthened to pursue a CS major" category were either sophomores or juniors. Representative quotes from students belonging to this theme include:

- *It has given me experience as well as encourage me to stay with computer science* - Male, Senior
- *It made me not want to change my CS major anymore* - Female, Sophomore
- *It made me more determined to get my degree in CSE* - Male, Junior

Encouraging exploration of CS careers and industries. Within this theme, we found that internships were allowing CS undergraduates to explore areas within CS as well as industries or work cultures within different types of companies. This exploration led 35% of 34 students (n=12) to determine their interests and dislikes. 58% of 12 students (n=7) whose responses were coded in this theme had a negative experience and wanted to avoid a CS area such as Information Technology or Web Development or a certain type of company or industry like military or an established corporation after their internship. On the other hand, 33% of 12 students (n=4) had a positive impact and wanted to work for the same company or a CS area. One student had both a positive impact to work in an area as well as a negative impact to avoid a certain area. Those who had a negative experience were willing to explore a different area in the future. Some representative quotes from this theme include:

- *It significantly affected my career goals. It made me more interested in simulation and in working for government contracted companies* - Male, Senior
- *I know more about what interests me and which fields of study to avoid* - Female, Sophomore
- *I have interned as an IT tech for a construction company. It made me not want to work in IT ever again* - Male, Junior

Promoting personal/professional growth. In this theme, students explained that internships helped them to grow personally as well as professionally. The personal growth was not only limited to an increase in their knowledge and skills, but the students' responses also pointed out evidence of growth in dispositional temperament including confidence and responsibility. This growth had an agentic influence on students' behavior helping them to pick future courses or decide CS specialization areas. The internship also provided them with an opportunity to get subsequent job offers.

- *[My internship] Taught me to teach myself things* - Male, Junior
- *I loved my internship. It finally made me confident about my abilities in computer science* - Female, Senior
- *Lead to the acquisition of a post graduate job* - Female, Senior

Developed awareness of professional expectations. CS students who participated in internships indicated that internships shaped their outlook on the tech industry, and they gained awareness about professional expectation in the industry. Students explained that internships provide them with a new perspective on working in the industry and their CS degree.

- *It allowed me to see what it was like working in a professional environment and how working in a company would be* – Gender not specified, Sophomore

- *It helped me understand how the industry works actually. I did realize that I might not want to do the work I was doing in my internship but look at something else* - Female, Senior

3.5.2 Students' perceptions of the effectiveness of their CS degree program

To gauge students' perception of their curriculum's strength in preparing them for the professional experiences, we asked them: *How well has the CS curriculum at the university prepared you for industry and/or research professional experiences?* We found two primary themes: *effective* and *needs improvement*. In addition, 9% of 38 students (n=3) who responded to this question were not sure about the program's effectiveness.

Effective. 47% of 38 students (n=18), considered the curriculum to be "effective" in preparing them for professional experiences. These students felt that the curriculum prepared them exceptionally or adequately for developing skills, securing jobs, or getting calls for interviews. Students also pointed out that the curriculum has prepared them to learn new topics, as well as advanced classes were effective in preparing them for the industry.

- *Pretty well I'd say. It has taught me to teach myself how to code in new languages at least* - Male, Senior
- *It has prepared me enough to land me a job [internship] at Lockheed* - Female, Freshman
- *Decently well, judging from interviews* - Male, Junior

Needs improvement. 45% of 38 students' responses (n=17) were categorized into the "needs improvement" theme. In this theme, students reported that the curriculum fairly or poorly prepared them for their professional careers. In addition, students found the curriculum to be more geared towards preparing them for graduate school or research, and several other students perceived their prior knowledge or self-initiatives to learn new languages and tools were necessary for preparing them for their future careers.

- *The curriculum is more geared towards students pursuing graduate school or research* - Male, Junior
- *Only somewhat. It's been mostly personal investment in different technologies. [University] only provides the "paper" that allows you to get in the door. The rest is on you* - Male, Sophomore
- *It gave me some good base knowledge of things, which is helpful. But all of the tangible skills that I have that actually earned me a job, were self-taught or taught to me by another entity* - Male, Junior

To better understand the CS students who reported that the curriculum needs improvement, we used their comments from several questions in the survey where they explained how academia was different from the industry (see Table 1). Thirteen students provided feedback on the distinction. We found two themes which answered RQ2. These themes included the *need for a broader curriculum* and *better alignment between languages, tools, and frameworks used in industry and academia*.

Need for a broader curriculum. Six CS students mentioned that the CS academic degree programs need more industry or job-related courses, and holistic improvement of pedagogical practices at the program level. The key issues students emphasized in this theme included offering more tech electives, fewer general education credits, optional hardware courses, and including practical applications in theory heavy courses.

- *Better balance of theoretical and skill driven CS skill and more app development classes* - Male, Junior
- *For my internship, I taught myself two languages and used little of what I learned in school. I wish the CS department would teach more real-world applications of code and teach both coding and concepts in lecture rather than deeply relying on concepts and letting you figure out the rest on your own* - Female, Senior

Better alignment between languages, tools, and frameworks used in industry and academia. Seven CS students stated that a programming language, framework, tool, or methodology used in academia was not used in the industry. They commented on the ubiquity of the agile software development model and less usage of languages like C++ and Java in the industry.

- *Another thing I think should be changed is the focus on C++. In my first couple years here, I thought C++ was this great language and it would come in handy to know it well since I was using it in multiple classes. Then, when I went to interview with companies, not a single one even touches the language. I think it's important to teach a C-based language to have that experience, but it should be limited to one class. There are so many other languages in which knowledge of them will actually benefit us, that we should be using* - Male, Junior

3.5.3 Student Strategies for Professional Success

Our third research question focused on the lessons students can learn from professional and academic experiences that can help other students for their professional success. 37 students responded to a question: *Reflecting on your degree experience, what advice would you give to students enrolled in this program to improve their experience in the program and their professional success?* We found 28 unique categories from 37 student responses. Three themes emerged from these categories: *Work outside curriculum, Be strategic in coursework, and Have social supports and a network*.

Work outside curriculum. In this theme, 54% of 37 students (n=20) recommended that their peers do work/learn outside the CS curriculum. Prominent strategies in this category included: learning outside school (n=8), getting involved with student organizations (n=7), doing side projects (n=6), learning to program for interviews and industry (n=5) and doing internships (n=4).

- *Do personal projects and get experience working on a team. Always strive to learn more* - Female, Sophomore
- *Do a lot of practice in your free time by visiting programming contest websites (SPOJ and the likes), watch YouTube videos, but most importantly GET INVOLVED* - Male, Junior
- *Sign up for the right professors, get an internship early, get really good at learning outside the classroom* - Male, Senior
- *I would encourage other students to get internships to experience what the computing field is actually like. The classes at university don't give a good indication of what it's like to work in the professional field at all* - Female, Sophomore
- *School is not enough to be successful in this field, you must learn a lot on your own and topics that are being discussed/introduced in the industry* - Male, Junior

Be strategic in coursework. In this theme, 54 % of 37 CS students (n=20) suggested strategies to follow during the CS degree program. Prominent strategies in this category included: taking courses offered by specific professors (n=6), working hard and not procrastinating (n=6), taking courses with projects and working hard in them (n=3), teaching yourself before classes (n=2), taking courses to determine interests (n=2) and taking electives in areas of interest (n=2).

- *Take a wide variety of courses early to find out what does and does not interest you. Don't seek electives that are easy, but rather interesting* - Male, Senior

- *Work hard on your projects and make sure to do a good job, as opposed to just doing what you need to do to get by. If you slack off you will have a lot of catching up to do before attending and interview or actually going to a job* - Male, Junior

Have social supports and a network. In this theme, 24% of 37 students (n=9) advised other students to make friends in CS/classes, talk to TA's and Professors, attend office hours, do networking, and take advice from seniors for professional success or a better CS degree program experience.

- *Make lots of connections. Make friends with your TAs, professors, and classmates. It makes the course so much more enjoyable and easier* - Female, Freshman
- *I would suggest them to talk to professors and their seniors and try various things in their initial years to figure out what they like and then focus on that field in the later years* - Female, Senior

3.6 Discussion and Conclusions

Our paper contributes to the CS professional development literature in the following ways:

Explaining the impact of internships on CS students' career goals. Our findings suggest that industry-based internships are playing a crucial role in retaining CS students in computing programs, promoting exploration of different areas of computing and computing careers, and intentional exploration of technical electives. This role is crucial as prior research has shown that CS students have misconceptions about computing and that many undergraduate students are not intentional about their selection of technical electives and courses [14, 62–64, 100]. In addition, our findings extend prior results from researchers at the Siena College [50] who found that a department-based CS internship program had a positive impact on student retention for upperclassmen. Despite the benefits students found from participating in internships, findings from our study give cause for alarm as only 41% of CS students in our sample participated in at least one internship experience. We have found that these numbers are similar across junior (44%) and senior years (42%). Results from a Gallup-Purdue Index revealed that 61% undergraduate students use career centers for internship search assistance [109]. Thus, further research is needed to better understand: (1) the characteristics that differentiate successful internship applicants from unsuccessful applicants and (2) why students, especially juniors and seniors have not had at least one internship experience, given that companies give preference to students who have had internship experiences for full-time jobs [109, 137, 165].

Analyzing students' perception of the effectiveness of CS degree programs in preparing them for their professional careers. Overall, we found mixed responses from students completing at least one industry experience: 48% of the students felt that the curriculum is effective, and 47% CS students felt that the curriculum needs improvement in preparing them for the internships. Nationally, one-third recent U.S. college graduates strongly agreed that their internship allowed them to apply what they were learning in the classroom [166]. Internationally, Tomar and Mishra [150] interviewed students in a prominent university in India and found similar patterns of mixed satisfaction and dissatisfaction with their CS degree program's preparation for industry experiences. Students in our study recommended that the CS curriculum needs to be broadened to include more courses in web or app development, more practicality and project-based learning coursework, the agile methodology of software development in coursework, and more relevant programming languages that are used in the industry. These findings confirm a prior study's finding on the perceptions of employers about the gaps between CS industry and academia that found employers reporting recent graduates to be struggling with software tools, ineffectively communicating with their co-workers and customers, and having a lack of project experience [130, 131]. These issues prevent students from gaining employment. This suggests that degree programs need to ensure that these gaps are minimized to better prepare our students for jobs in the industry and thereby satisfy the demand for CS graduates in the industry. Additionally, the findings suggest that computing academic programs offer different communities of practice [152] than what students' experience during an internship and one avenue that may act as a bridge between these two communities is computing clubs which focus on skill and professional development.

Identifying the strategies that CS students recommend for professional success. Overall, we found that students were working outside academia to gain additional skills needed to secure an internship or a full-time job. Moreover, they were recommending these strategies to other students. Thus, we need to better understand what skills students are gaining outside of our curriculum to help them secure industry internships. Then we need to evaluate which skills and experiences we can integrate into our coursework so that all students can benefit from it and are provided with access to such resources in every university. We also found that students are strategically working within their degree program and are forming a social support system consisting of friends in their major and professors and TAs, as well as are networking to attain professional success and be prepared for their professional careers.

Recommendations. Based on our findings, we recommend that students pursue at least one CS internship prior to completing their CS degree program. We also suggest that departments make internships mandatory for CS degree graduates given the role they play in students' professional development as well as the industry's predilection towards applicant's prior experience in the new graduates' recruitment process. Further, we recommend that departments ensure that their CS curriculum is effective in balancing theoretical and practical applications in computing, thereby preparing students for industry jobs, and reducing the demand for lack of CS graduates for technical jobs in the industry.

3.7 Limitations

The findings from this study represent a snapshot of the internship experiences taken from a small sample of CS students at a large US-based R1 university. Hence, the findings may not generalize to large populations of students at similar or different institutions or experiences of CS students in other countries. In the future, additional data on students' GPA, type of internship - paid or unpaid, area of internship and type of company they worked for, might help to better characterize the population. Additionally, our sample consists of students who are enrolled in computing programs and are prone to survivorship bias. There is a chance that students who left the computing discipline may have had negative experiences in industry and are not present in our sample. Future investigations can explore the students' experiences in industry who left a computing major or the discipline altogether. Another limitation of our study is that qualitative analysis relies on interpretation, which can introduce subjectivity. Different researchers may interpret the same data differently, leading to variations in findings. However, to improve validity and reliability, we have described our thematic analysis process and provided participant quotes for transparency. Lastly, given that this study gave students extra credit at the end of the semester, the study population could be skewed towards high performing students that wanted to take every opportunity to secure a good grade in their course or low performing students that wanted an extra grade boost.

3.8 Subsequent Study

From this study, we learned that internships play a crucial role in helping computing undergraduate students to commit to CS majors, degrees, and careers, understand professional expectations, explore the discipline, and provide authentic opportunities for self-evaluation. However, only a minority of students (41%) in our sample participated in an internship before graduation. Therefore, we did preliminary analysis on the data collected from this study to understand the characteristics of CS students who have interned at one or more companies and those who have not interned. This analysis was presented at the ACM SIGCSE 2019 conference as a part of the graduate ACM student research competition [73] where we found differences in students' career goals, participation process in external activities such as undergraduate research experiences or student clubs, and preparation practices for securing internships between students who interned and those who did not. This work was awarded second place in the graduate category at the competition. To collect more evidence to corroborate our findings, we designed a subsequent multi-institutional study, targeting a larger sample, to empirically investigate the differences between students who secured internships and those who did not which is described in the next chapter.

4. Study 2: Who is participating in internships and how?

Given the benefits computing students were receiving from internships (Chapter 3), it was concerning that only a minority of students (40%) were participating in internships. Therefore, we wanted to investigate how students were participating in internships. Specifically, my dissertation will answer the following research question: *How do computing undergraduate students **secure** and participate in internships? What **barriers** prohibit them from participating in internships?* This chapter will describe preliminary analysis regarding this research question, and I will highlight the findings from three papers describing students who participate in internships, students who do not participate in internships, and the factors that are associated with students' participation in internships.

My advisor, Dr. Christina Gardner-McCune, and I applied for the SIGCSE Special Projects Grant to scale the CS Identity project in May 2018 and assess students' professional identity formation in the context of academic programs, professional development opportunities, and informal learning avenues. We were awarded a grant for the "*CS Identity Development Interview Project*" in June 2018, and we planned and ran our second study between August 2018 - December 2019. This study was multi-institutional and used mixed methods (surveys, interviews, and artifacts: resumes). Data was collected from 767 students who participated in a survey and 42 students who were purposefully recruited for semi-structured interviews at the University of Florida, Georgia Institute of Technology, and Rose-Hulman Institute of Technology. These institutions were selected to understand how student participation in internships varied across two similar large R1 public institutions and one dissimilar small private undergraduate teaching focused institution. We analyzed the survey data collected from this study from 2019 and our results and findings were published in the following conference proceedings under the research papers category between 2019-2023 during my time in the HCC Ph.D. program:

1. ***Paper 1 Who Participates and Preparation Practices**: Exploring the Participation of CS Undergraduate Students in Industry Internships* at the ACM SIGCSE TS 2020 Conference (Technical Symposium on Computer Science Education) [80].

2. ***Paper 2 Barriers to Participation**: Barriers to Securing Industry Internships in Computing* at the ACM ACE 2020 Conference (Australasian Computing Education Conference) [72].

3. ***Paper 3 Factors Influencing Participation**: Modeling Determinants of Undergraduate Computing Students' Participation in Internships* at the ACM SIGCSE TS 2023 Conference [155].

I was the lead author on the first two papers and Dr. Gardner-McCune was the supervisor and co-author. For the third paper, focused on the survey data analysis, I supervised two undergraduate senior projects for Megan Wolf and Charlie Hobson who were the first and the third authors, while I was the second author. For this paper, I contributed to the literature review, data collection, analysis, and writing. The interview data from this study will be analyzed as a part of the proposed work and will be described in Section 6.

The remaining chapter is organized as follows. For each section, I have consolidated respective sections from the three papers to avoid redundant text given the overlaps in introduction, related work, and theoretical grounding. For methods, findings, and discussion sections, I divide the sections into subsections highlighting my approach and analysis for each paper.

4.1 Introduction

Jobs in computing are projected to grow at 13% annually over the next decade in the United States [167]. This growth is widening the gap between the number of computing jobs available in the industry and CS graduates required to fill these jobs [163]. The rising enrollments in computing majors [25] have ameliorated the situation to a certain extent, but the demand for CS graduates is outpacing the number of enrolments in the computing majors. Moreover, it is a cause for concern that recent CS graduates might be underprepared for jobs in the industry as the underemployment rates for computing jobs held at 26% in 2018 [164]. This under preparation further exacerbates the existing gap between the supply and demand of potential computing hires. In lieu of this under-preparedness, employers have noted that recent CS graduates lack technical competence and professional skills for pertinent jobs in the industry [20, 130, 131]. One mechanism that allows students to gain these technical and professional skills is through their participation in internships during their degree program. Internships provide students an opportunity to engage in experiential learning that enhances their intellectual, personal, professional, and ethical growth [51, 138, 147]. In addition, internships allow students to explore computing pathways, determine likes and dislikes, develop professional skills, and build professional networks in a conducive environment [77, 162]. Employers also use internships as an opportunity to evaluate potential candidates, thus deeming them crucial to the full-time recruitment process [109, 137]. Therefore, encouraging students to participate in internships may be an effective strategy for preparing students for jobs in industry and reducing the skill-deficit. However, little is empirically known about computing students' participation in industry internships and the preparation process they use to successfully secure an internship.

In this section, we present findings from our multi-institutional study aimed at understanding the participation of computing students in internships and analyzing the differences between students who intern and those who do not. We surveyed 767 computing undergraduate students across three universities in the United States and identified (1) the students that participate in internships, (2) the students who do not participate as well as the impediments they face when failing to secure an internship, (3) the differences in preparation process of students who intern and students who do not intern, and (4) the factors that associate with students' participation in internships. We analyzed the quantitative data using descriptive and inferential statistical methods as well as modeled student participation in internships using a multivariable logistic regression model. The open-ended qualitative data from our survey was analyzed using inductive thematic analysis.

Overall, we found that 40% of students participate in at least one internship. Demographically, equal proportions of males and females interned. Using a logistic regression model, we found that (1) year in school, (2) household income (a proxy for socioeconomic status), (3) involvement in activities outside the curriculum, and (4) lower identity diffusion scores (i.e., low exploration and low commitment) are significantly associated with a student's participation in an internship. Quantitatively, there were no significant differences between students who intern and those who do not with regard to academic performance. However, through thematic analysis, we found differences regarding students' preparation process for securing internships. Interns explicitly prepared by practicing technical interview questions and dedicating time to career preparation. Students who did not intern were less involved in the application process, relied on coursework for securing internships, and were not applying for internship positions due to alternate priorities or less developed agentic resources such as low self-efficacy. These findings suggest that factors outside of coursework are influencing students' ability to secure internships. The results of this study contribute to computing education research (CER) literature empirical results associated with computing students' participation in internships. Our work can inform CS departments about student barriers to internship participation and aid in the development of support programs focused on improving students' employment outcomes.

4.2 Related Work

4.2.1 Professional development opportunities for computing undergraduate students

Employers have reported that recent CS graduates lack technical abilities, personal skills, and professional qualities [130, 131]. One way to improve these skills without burdening our existing curriculum is by supplementing our degree programs with professional development activities that provide students an opportunity to develop these skills through experiential learning [88]. Research in professional development for computing undergraduate students has focused on the professional development of students through participation in capstone courses [116–118], co-curricular activities [49], project-based courses [43], local community-service projects [42], part-time or remote internships [42], student experiences in industry internships [113], or work-integrated learning programs developed through industry-academia partnerships [26, 50]. This research includes Parker's study which found that software engineering capstone courses allowed CS students to explore CS career options [116–118]. In another study, Fryling et al. [50] found that a department-scaffolded internship program at Siena College had a positive impact on CS students' retention. Research on professional development through CS industry internships is limited. This research includes inquiries on understanding the role of internships in professional identity formation [97, 150] or exploring students' experiences of participation in an internship [24, 77, 106, 162]. However, there is a lack of research in the CS education research literature that focuses on gaining insights into who are the students that participate in internships and the barriers faced by those who fail to participate.

4.2.2 Benefits of internships in computing

Industry internships are a valuable method of gaining technical and professional skills beyond what is taught in formal academic computing classrooms. In addition, internships provide opportunities for self-evaluation, expansion of professional networks, and development of professional expectations [77, 106]. Thus, internships provide an authentic environment for addressing the industry-related skill deficit [20, 130, 131] among computing students. In addition to supporting students in skill building, internships have been shown to foster identity formation [44, 79], increase retention in computing programs [50], and improve capstone project quality [68, 113]. Lastly, employers often utilize internships as evaluation tools during the recruitment process for hiring decisions, and students who previously have interned are more likely to get a full-time position and a higher starting salary [109, 137, 143, 165]. In summary, internships have been found to provide computing students with opportunities for skill building and participation in internships is beneficial for securing subsequent employment after graduation. Thus, it is highly recommended that students participate in internships before graduation.

4.2.3 Computing internship recruitment process in the United States

Students can apply for internship positions in various computing disciplines including software engineering, web development, user experience design, data science, and computer networks. These positions include co-op's, paid, and unpaid internships. The type of companies ranges from working at startups or local companies like Gainesville Regional Utilities (GRU) to established companies like Google and Amazon. The internship positions are competitive, and employers make hiring decisions through a multi-stage competitive recruitment process [98]. The process typically has three stages: an application phase, an interview phase, and a negotiation phase.

During the application phase, an applicant applies to various roles and companies by submitting their resumes and answering questions through digital applications, career fairs, or company information sessions. The applications are screened through Applicant tracking systems (ATS) which select candidates based on keywords in a resume, employee referrals, or manually selecting candidates after interactions at career fairs and company information sessions. Relevant candidates are selected for the next stage which is the interview phase based on a student's experience, GPA, and involvement in projects [98, 143]. Companies invite applicants for one or more technical and behavioral interviews and there is variation in the number and rigor of the interviews depending on the job role and companies. A majority of companies ask students technical questions in an interview related to DSA, especially for software development and engineering positions. In these interviews, applicants are asked to either write programs on whiteboards or shared screen text editors and talk out loud about their thought processes when solving a problem [98, 143]. Applicants are evaluated on problem-solving skills, professional skills such as communication skills, and the ability to derive correct solutions in a limited timeframe [10, 143]. Finally, in the third stage, an offer is made by the company and the applicant has an opportunity to negotiate. Some universities require students to pursue an internship before graduation while others have no such requirement.

4.2.4 Modeling factors associated with internships

Work that quantitatively modeled students' internship participation includes a study by Hoekstra which modeled variables that predict internship participation across different undergraduate majors [65]. Her work found five significant pre-college predictors (race, gender, age, first-generation status, and future educational plans) and participation in high-impact practices such as research, learning communities, etc. influenced internship participation. According to her study, students who were Asian American, male, older, first-generation, or had lower participation in high-impact practices were less likely to have interned. Hoekstra's findings provide insight for building our model and we used several similar predictors. While Hoekstra's study generalizes across majors, we aim to extend this work by performing a similar analysis on the unexplored field of computing. Further, we include variables specific to CS curriculum and involvement as well as identity status scales as predictors.

Internship participation has also been modeled in other fields including civil engineering [55] and medical sciences [54]. These studies determined potential predictors of students' satisfaction with internships [55] or modeled attributes that determine student success in internship performance [54]. Generically across majors, researchers have also predicted final grades and degree level classification from internship experience [15] or analyzed the impact of internships on university graduation rates [70]. In contrast, our study models the inverse of these relationships as we seek to understand if higher grades or other variables are predictors of securing internships.

Researchers have also studied the relationship between identity formation and internships and have found that internships support identity formation in engineering [44] and counseling psychology [47]. Our work tries to understand the inverse relationship between identity formation and participation in an internship and we assess if a student in an identity status is more likely to have secured internships. A study in Psychology by den Boer et al. [18] investigated the association between identity formation and internship participation and found that an internship in itself did not explain individual differences in identity processes, and enrollment in an internship was largely unrelated to identity processes, i.e. there is no relationship between internship participation and identity formation. den Boer et al.'s work is similar to our study, but the authors recruited graduate students who were interns and undergraduate students who did not intern, and internship enrollment was an obligatory part of their curriculum. Our work pertains to the computing discipline, and we compare a more homogeneous population of undergraduate students who have or have not participated in internship(s). In addition, internship participation is optional in our program and hence our results might not be comparable with den Boer et al. as the population and context for the studies are different. Our results may be held in similar computing programs where internship participation is not obligatory.

4.3 Methods

4.3.1 Study design and research questions

We designed a cross-sectional multi-institutional study based on a Concurrent Triangulation Design [40] to understand how computing students participate in internships and other professional development activities through a survey and semi-structured interviews. In this design, both qualitative and quantitative data is collected concurrently but is analyzed separately and then combined to triangulate overlapping patterns [40]. This design supports the corroboration of findings through multiple data sources and improves validity. Our study was designed in Spring 2019 after a single institution pilot study in Spring 2016 [74, 77] that is discussed in Chapter 3. This study is multi-institutional and has a larger sample size (5.5x) compared to our pilot.

For this section, we focus on the analysis of our quantitative and qualitative survey data and compare CS students who interned and those who did not. The interview data will be analyzed as a part of the proposed work. We address the following research questions in this section:

Paper 1 (who participates and preparation practices):

RQ1. Who are the computing undergraduate students that participate in industry internships?

RQ2. How does the preparation process of computing undergraduate students who secure an internship differ from those who do not intern?

Paper 2 (barriers to participation):

RQ3. What barriers do computing undergraduate students, who do not intern, encounter in securing an industry internship?

Paper 3 (factors influencing participation):

RQ4. What are the factors that influence undergraduate computing students’ participation in internships?

4.3.2 Population, sample, and research sites

Our study population is traditional college students who are enrolled in an undergraduate CS-related major in the United States. Our sample is drawn from students enrolled in an undergraduate computing degree program at three universities in the US and focused on four-year CS programs targeting students across academic standing, gender, and racial/ethnic diversity. Site A, the University of Florida is a large public research university in the Southeast and offers CS, Computer Engineering (CE), and Digital Arts and Sciences (DAS) majors through the CS department. The students can choose a major when they start college but can change it at any time. Site B, the Georgia Institute of Technology is another large public research university in the Southeast which was chosen to compare the trends at two similar types of institutions. At Site B, undergraduate students can choose to major in CS or Computational Media and can specialize in a self-selected CS sub-discipline. Site C, the Rose-Hulman Institute of Technology is a small private undergraduate engineering college in the mid-west. This site was chosen to compare the trends with a different type of institutional environment. This site offers students to major in CS, International CS, or Software Engineering (SE). At all three research sites, admission in undergraduate degree programs is competitive and participation in industry internship(s) before graduation is not mandatory.

4.3.3 Participant recruitment

Our study was approved by the Institutional Review Board at the research site. Survey participants were recruited from Site A's CS1, CS2, software engineering, human-computer interaction, and operating system courses. The students in these courses were given 1% extra credit towards their final grade for participating. Students from Site B were recruited from a CS seminar course. They were also offered 1% extra credit. For Site C, we recruited students through a recruitment email on their department listserv. We offered gift cards to every 40th respondent at Site C and this option was also available at Site A and Site B if they chose to opt-out of extra-credit. A substitute assignment requiring equal effort was also provided to the students if they did not wish to participate in our research study for extra credit.

4.3.4 Participants

767 students at the three research sites responded to our survey excluding duplicates in Spring and Fall 2019. There are differences in the dataset for the three papers based on the time of data collection and publishing dates of the articles as well as the alignment of the data to our research questions. For example, the corpus used for analysis for our SIGCSE 2020 and ACE 2020 papers, was from the data collected in Spring 2019 as the data collected in Fall 2019 was ongoing during article submission at the respective conferences. For the third paper (SIGCSE 2023), the corpus consisted of data from both Spring and Fall 2019. We further curated the corpus for the second paper to answer the research question: *What barriers do computing undergraduate students, who do not intern, encounter in securing an industry internship?* discarding data from students who participated in internships for the analysis. We will now describe the corpuses of each of the three papers.

Table 4. Academic Standing & Gender of Participants (N=536) as reported in Kapoor & Gardner-McCune (SIGCSE 2020)

Academic Standing (By Year)						Gender		
1	2	3	4	5-6	Others*	M	F	Others**
31.9% n=171	19.2% n=103	28.2% n=151	14.9% n=80	4.1% n=22	1.7% n=9	74.2% n=398	25.2% n=135	0.6% n=3
*Post-baccalaureate, transfer students, or pursuing a second bachelors. **Two students did not specify gender and one student identified them as agender.								

Table 5. Racial/Ethnic Identity of Participants (N=536) as reported in Kapoor & Gardner-McCune (SIGCSE 2020)

White	Asian	Hispanic or Latinx	African American	Others*
45.7% n=245	26.1% n=140	19.2% n=103	6.2% n=33	2.8% n=15
*Multi-racial (5), Native Hawaiian (3), Did not specify (2), Middle Eastern (2), Iranian (1), Arab(1), and Haitian American (1)				

Participants in the corpus for RQ1 and RQ2 reported in Paper 1 (who participates and preparation practices): 663 students responded to our survey by Spring 2019 and completed at least 5% of the survey (Total Response Rate: 44.0% at Site A and 18.4% at Site B). From these 663 students, the following were discarded: 53 students who completed less than 80% of the survey, four graduate students enrolled in an undergraduate course, 13 students who completed the survey twice (the submission with the maximum completion time was not discarded), 56 students who were not majoring/minoring in a CS discipline, and one student who did not specify whether they interned or not. Therefore, we were left with 536 students who completed more than 80% of the survey (Average Completion Rate=99.8%) and formed the corpus for our Paper 1. Of these 536 students, 485 were enrolled at Site

A, 44 at Site B, and seven at Site C. The students comprised 362 CS majors, 118 CE majors, 21 CS double majors, 19 CS minors, 13 DAS majors, and three SE majors. The average age of respondents was 21.1 years (SD=3.75, Min=17, Max=52). Other demographics are shown in Table 4 and Table 5.

Participants in the corpus for RQ3 reported in Paper 2 (barriers to participation):
From the corpus of the previous paper (N=536), 7 students were further discarded form 536 students due to lack of relevant responses from students that answered the RQ3 (*What barriers do computing undergraduate students, who do not intern, encounter in securing an industry internship?*). Therefore, we were left with 529 students who completed more than 80% of the survey (Average Completion Rate=99.8%). Of these 529 students, 60.7% of the CS undergraduate students (n=321) reported that they never interned during their undergraduate studies or were not hired by an employer the summer following our study for an internship. Specifically, 62.3% of the 485 students at Site A (n=302) and 43.2% of the 44 students at Site B (n=19) did not intern. The remaining 208 students at the two institutions previously interned or were interning the summer following our study. These 208 students were also excluded as they are not relevant for answering our research question. Further, 19 of the 321 students who did not intern were excluded as they did not respond to the qualitative question on our survey. Thus, we were left with 302 CS undergraduate students who never participated in an industry internship and answered the pertinent questions in our survey which formed the corpus for this paper.

Of these 302 students, 285 students were enrolled at Site A and 17 at Site B. 276 were full-time students, 22 were part-time, three were post-baccalaureate, and one was an exchange student. The students comprised: 207 CS majors, 65 Computer Engineering (CE) majors, 10 Digital Arts and Sciences (DAS) majors, 10 CS minors, nine CS double majors, and one unspecified major. The average age of respondents was 21.1 years (SD=4.1, Min=17, Max=43). The average GPA of respondents was 3.44 on a scale of 4.00 (SD=0.47, Min=1.40, Max=4.00). Other demographics are shown in Table 6 and Table 7.

Table 6. Academic Standing & Gender Identity of Participants (N=302) as reported in Kapoor & Gardner-McCune (ACE 2020)

Academic Standing (Year) †						Gender		
1	**2**	**3**	**4**	**5-6**	**Others***	**M**	**F**	**Others****
43.1% n=130	17.2% n=52	23.2% n=70	11.3% n=34	2.6% n=8	2.6% n=8	73.8% n=223	25.5% n=77	0.7% n=2
*Post-baccalaureate, transfer students, or pursuing a second bachelors. **One student did not specify gender and one student identified them as agender.								

Table 7: Racial/Ethnic Identity of Participants (N=302) as reported in Kapoor & Gardner-McCune (ACE 2020)

White	Asian	Hispanic or Latinx	African American	Others*
43.0% n=130	29.5% n=89	20.2% n=61	5.6% n=17	1.7% n=5
*Multi-racial (1), Native Hawaiian (1), Middle Eastern (1), Arab (1), and Did not specify (1).				

Participants in the corpus for RQ4 reported in Paper 3 (factors influencing participation):
For this paper, data was used from students at Site A (University of Florida) which was collected in Spring and Fall 2019. Data from Site B and Site C was excluded as the survey deployed at those sites did not have identity measures to reduce the length of the survey. These identity metrics were introduced in the model for determining the relationship between internship participation and other factors.

698 students responded and consented to our survey at Site A after excluding 41 duplicates. The response rate was 43% (N=698, total course enrollments=1620). From this dataset, the following were discarded: students who were not pursuing CS-related majors or were CS minors (n=78), students who completed less than 80% of the survey (n=20), students who were not in our undergraduate program (n=15), students without gender classification (n=2), non-traditional students over age 24 (n=45), and students with a high proportion of relevant missing data (n=20). Decisions to discard data were made for the following reasons: (1) we were trying to assess students' participation in internships who were enrolled in computing programs and represented traditional college students, (2) lack of data on a metric that was crucial for our analysis, and (3) inadequate representation of a certain population in our sample. Thus, our final corpus for Paper 3 consists of 518 students who were enrolled in CS (66%), CE (26%), DAS (4%) or double (4%) majors. The average age of the respondents was 20.2 (Min=18, Max=24, SD=1.4). Other demographics are shown in Table 8 and are representative of the student population in the CS program at respective institutions.

Table 8. Demographics of students in our corpus (N = 518) as reported in Wolf et al. (SIGCSE 2023)

Year					Gender		Race/Ethnicity				
1	2	3	4	5-6	M	F	White	Asian	Hispanic /Latinx	African American	Other
27%	18%	32%	17%	5%	73%	27%	47%	25%	20%	6%	3%

4.3.5 Data collection

We gained consent from the Institutional Review Board at Site A for a multi-institutional online survey administered over Qualtrics. On average, the students completed the survey in 37.3 minutes. The survey consisted of 11 sections (maximum of 74 questions due to display logic): Consent, Institution and Extra-credit, Demographics, Professional Goals, Professional Identity, Industry, Degree Experience, Social Supports, Professional Development, Advice and Suggestions, and Documents and Follow-up. These 74 questions were of three types: 49 multiple-choice questions (MCQs), 10 short-response questions, and 15 open-ended responses. All questions were optional and were either developed from the findings of our pilot study [73, 74, 77] or were taken from the following three sources: NCWIT Student Experience of the Major Survey [110], and CRA Data Buddies Survey [168], and the revised version of Bennion and Adams' Extended Objective Measure of Ego Identity Status (EOM-EIS) validated instrument [12] which consisted of measures to quantify Marcia's identity statuses [96]. The mapping of our research questions to the survey questions for the three papers is shown in Table 9.

Paper 1 (who participates and preparation practices). In this paper, we focused our analysis on 486 student responses on an open-ended question from the industry section and 536 student responses on nine multiple-select questions from the Demographics, Industry, and Professional Development sections. The open-ended question was "*How did you prepare or how are you preparing to get an internship?*" and the nine factors were gender, racial/ethnic identity, academic year, household income, employment status, participation in internship, participation in technical interviews, time devoted to career development, and GPA.

Paper 2 (barriers to participation). For this paper, we focused our analysis on 302 student responses on an open-ended question from the industry section and three factors from the demographics (gender and academic year) and industry sections (participation in an internship) to describe the context. The open-ended question in the survey that we use for our analysis was: "*Why haven't you interned so far?*" and this question was displayed to students who selected that they had not interned previously or were not participating in an internship the summer following our study.

Table 9. Survey Questions to Answer Our Research Questions as reported in Wolf et al. (SIGCSE 2023)

Paper	Research Question	Survey Section	Survey Metrics/Questions
Paper 1 (who participates and preparation practices)	RQ1. Who are the computing undergraduate students that participate in industry internships?	Demographics (5) Industry (1)	Year, Gender, Employment Status, Household income, Race/ethnicity, Internship Participation
	RQ2. How does the preparation process of computing undergraduate students who secure an internship differ from those who do not intern?	Demographics (1) Industry (2) Professional Development (2)	Internship Participation, GPA, Time on preparation, and practicing interview questions
			How did you prepare or how are you preparing to get an internship?
Paper 2 (barriers to participation)	RQ3. What barriers do computing undergraduate students, who do not intern, encounter in securing an industry internship?	Industry (1)	Why haven't you interned so far?
Paper 3 (factors influencing participation)	RQ4. What are the factors that influence undergraduate computing students' participation in internships?	Demographics (8) Identity (4) Professional Development (1) Industry (1)	Household income, Race/ethnicity, Gender, Age, Employment status, GPA, High school courses in CS, Year in school, Diffusion score, Foreclosure score, Moratorium score, Achievement score, External involvement score, Internship Participation

Quantitative Question (Multiple Choice) Qualitative Question (Open-ended)

Paper 3 (factors influencing participation). In this paper, we focused our analysis on 14 multiple-select questions from the Industry, Demographics, Professional Identity, and Professional Development sections. These survey question metrics and types are further described in Table 10. We selected these questions for the following reasons: (1) our approach to analysis is quantitative and hence we discarded open-ended questions, (2) the question was irrelevant for answering our research question, and (3) the question provided background information on the sample or context for replication. Our response (dependent) variable for this paper is a binary categorical variable representing participation in internship(s) or co-op(s) during a student's enrollment in a degree program (not counting internships during high school). We asked students if they had previously interned or were going to participate in an internship in the upcoming summer (they already received an offer). If the student answered yes to either of these choices, they were coded as "yes" as we are trying to understand students' ability to secure internships. We used 13 explanatory or independent variables (described in Table 10) in our model to identify their associations with a student's participation in an internship.

Eight of our explanatory variables were single-item measures such as Gender or GPA. The remaining five variables consisted of multiple-item measures. These multiple-item measures were aggregated to form scores representing four identity status variables and one variable called *External Involvement* which denotes a composite score for a student's involvement in activities outside the classroom such as hackathons, conferences, research, and student clubs, etc. For the *External Involvement* variable, we collected information on how frequently a student participated in activities outside the classroom using an ordinal scale for each activity ("Never {coded to 0}", "Once {1}", "2-3 times {2}" and "4 or more times {3}"). The composite score for each student was computed by aggregating the numerically coded responses of participation frequencies in all activities. For example, if a student stated that they participated in 2 of the 14 activities (e.g. personal projects and clubs), and they participated in each of them “Once” (coded as 1), their *External Involvement* score was 2 out of a maximum possible score of 42 (14 x 3).

Table 10. Explanatory (independent) variable descriptions as reported in Wolf et al. (SIGCSE 2023)

Variable Category	Independent Variable	Description (Coded value)
Demographic and Socioeconomic Factors	Household income ★	{“Less than $20,000” (1), “$20,000 to $34,999” (2), “$35,000 to $49,999” (3), “50,000 to $74,999” (4), “$75,000 to $99,999” (5), “$100,000 to $149,000” (6), “Over $150,000” (7)}
	Race/ethnicity ▲	{White/Asian (0), Underrepresented: all other ethnic and racial representations (1)}
	Gender ▲	{Male (0), Female (1)}
	Age ■	Numerical (Range: 18-24)
	Employment status ▲	{Unemployed (0), Employed - working along with the degree program (1)}
Academic Profile	GPA ■	University-level grade point average on a 4.0 scale
	High school courses in CS ▲	{No (0), Yes (1)}
	Year in school ★	{Freshman (1), Sophomore (2), Junior (3), Senior (4), Super Senior (5)}
Identity	Diffusion score ⊙	Marcia identity status composite score (scale: 6-30): Low exploration, low commitment
	Foreclosure score ⊙	Marcia identity status composite score (scale: 6-30): Low exploration, high commitment
	Moratorium score ⊙	Marcia identity status composite score (scale: 6-30): High exploration, low commitment
	Achievement score ⊙	Marcia identity status composite score (scale: 6-30): High exploration, high commitment
External Involvement	External involvement score ⊙	Composite score based on involvement in 14 activities, e.g. hackathons, clubs, etc.(scale: 0-42)
Key: Binary encoded categorical ▲ | Ordinal encoded categorical ★ | Quantitative ■ | Quantitative variable computed from ordinal scale questions ⊙		

Four MCQs in our survey that pertained to Marcia’s identity statuses measured using the EOM-EIS instrument consisted of multiple items for an *identity status* (six 5-point Likert statements per status, 24 statements in total). For measuring each status, the scale included two statements that gauged *identity status* in relation to occupation, recreational activities, and lifestyle [12]. Thus, each status had a corresponding variable representing the aggregate of six ordinally coded 5-point Likert statements (Strongly disagree: 1 to Strongly agree: 5) and had a range between 6 - 30. A higher value in a status scale implies a higher likelihood for a student to be in that status. We computed Cronbach’s alpha, a measure of internal consistency of a scale that measures a latent variable (in our case each *identity status* was a latent variable). Cronbach’s alpha measures how closely related a set of single-measure items are as a group. For our sample, Cronbach alpha coefficients were 0.64 for diffusion status, 0.83 for foreclosure, 0.61 for moratorium, and 0.62 for achieved status. While Cronbach alpha coefficient values of 0.70 or greater are an indicator of high reliability of an instrument in social sciences [144], Pallant argues that variables measured with less than 10 items generally have lower values of Cronbach’s alpha [115]. For each status, we used six statements, and hence the lower values of the coefficient could be attributed to the lower number of items in our scale. Moreover, the range of values for our Cronbach's alpha coefficients was in line with the original EOM-EIS instrument [12] as well as subsequent studies that used this scale in other domains [91]. Hence, there is a possibility that scales for measuring complex identity statuses have lower internal consistency than other constructs.

4.3.6 Data imputation and preprocessing for modeling factors associated with internship participation (RQ4)

Our final data corpus for Paper 3 (factors influencing participation) consisted of missing data as all questions in our survey were optional. Before feeding data into the model, we had to deal with missing data and multicollinearity. The total missing data for explanatory variables we imputed in this paper was 1.4% (n=326, N=23828 total data points). Given that the overall missing data was relatively low (1.4%) when compared with the number of responses that had some missing data point (40%), we decided to impute data rather than discard the incomplete responses. At a granular level, we imputed data (replaced missing values with substitute) for the following explanatory variables: GPA (n=19, N=518, 3.6%), age (n=43, N=518, 8.3%), household income (n=47, N=518, 9.1%), identity achievement (n=5, N=3108 single-item measures, 0.2%), identity diffusion (n=9, N=3108, 0.3%), identity foreclosure (n=5, N=3108, 0.2%), identity moratorium (n=12, N=3108, 0.4%), and external involvement score (n=186, N=7252, 2.6%). We used imputation techniques depending on the type of the missing data (i.e., quantitative or categorical) and the skewness of a variable's distribution. It is recommended to not replace missing values with the mean for skewed data distributions because outliers are more likely to influence the mean, therefore we utilized either the median or mode [3]. We used the seaborn python library to plot a kernel density estimate and histogram with bins. We observed that the GPA distribution and household income were skewed towards the left, the external involvement score and age were skewed right, and identity scores were all slightly skewed (see Figure 1). As such we imputed missing values for numerical explanatory variables such as GPA, age, or scores with the median values and used the mode for household income which is a categorical explanatory variable.

Multicollinearity. Before conducting regression analysis, we also explored the possibility of correlations between our explanatory variables to limit the possibility of introducing multicollinearity in our model. Multicollinearity can lead to higher variance, overfitting, and difficulty in model interpretation due to instability in the magnitude of regression coefficients [56]. If a regression model is composed of two or more predictors that are moderately or highly correlated, multicollinearity exists. A common method for checking if multicollinearity exists in a model is checking for high correlations among pairs of predictor values. In our study, we check for correlations among the predictors using Pearson's R for continuous vs. continuous cases, Correlation Ratio for categorical vs. continuous cases, and Cramer's V or Theil's U for categorical vs. categorical cases using code modified from the dython library which provides data analysis tools in python [169]. We consider correlation coefficients with a magnitude greater than ±0.7 to be highly correlated [108]. Also, we calculated the variance inflation factor (VIF) as an additional collinearity diagnostic metric [56]. A general rule is that if the VIF score for a predictor is greater than 5, it is recommended to remove one of the correlated explanatory variables to limit multicollinearity. The VIF values for predictors were below the threshold and ranged from 1.06 to 2.98. However, age was highly correlated with the year in school (Pearson's R = 0.80) and hence we excluded age as a predictor in our model.

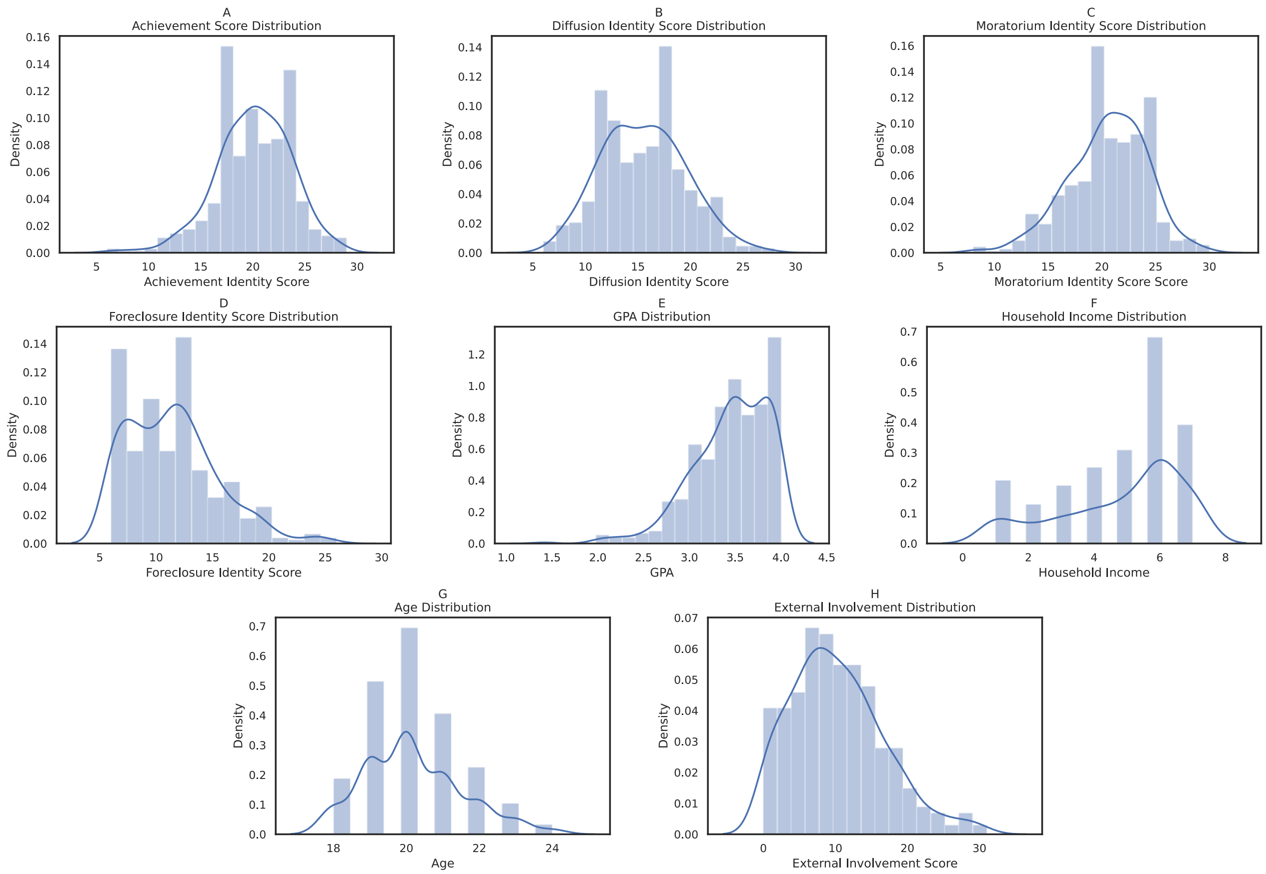

Figure 1. Distributions of imputed variables as reported in Wolf et al. (SIGCSE 2023): *Identity Statuses* (A-D), *GPA* (E), *Household income* (F), *Age* (G), *External Involvement* (H)

4.3.7 Data analysis

Qualitative Analysis. For RQ.2 (*How does the preparation process of computing undergraduate students who secure an internship differ from those who do not intern?*) and RQ.3 (*What barriers do computing undergraduate students, who do not intern, encounter in securing an industry internship?*), we analyzed open-ended student responses using thematic analysis based on an inductive approach [19] in Microsoft Excel. We started with the raw data and created codes inductively using words from participant responses. The first author created primary codes which were then clustered to form categories, and these categories were combined into themes. The authors discussed the themes in which there was disagreement until a consensus was reached about the theme accuracy and reliability. The data was then recoded. This was followed by a frequency analysis of unique participant responses within each theme. We counted unique participants when computing these frequencies, to avoid counting multiple responses from the same participant within any theme. Some participants' responses belonged to more than one theme and thus the percentages don't add up to 100%.

Quantitative Bivariate Analysis. We used descriptive and inferential statistics to answer RQ.1 (*Who are the computing undergraduate students that participate in industry internships?*) and RQ.2 (*How does the preparation process of computing undergraduate students who secure an internship differ from those who do not intern?*) . The quantitative bivariate analysis was limited to the multiple-choice questions and was conducted in IBM SPSS 11. We divided the data set into two groups: students who did not intern and students who interned or were interning the summer following the study for the first time. The students who interned or were interning the summer following the study were merged into one group as we are trying to understand students' ability to secure an industry internship and what makes them different than those who do not secure an internship. We ran two types of statistical tests based on the type of variable to assess statistical significance and we also report practical significance through the appropriate effect size measure. We used $p<=0.05$, $\alpha=5\%$ to reject our corresponding null hypothesis. Also, when conducting tests, we excluded extreme groups (e.g. other genders, n=3) as we did not have an adequate representation for that level of the nominal variable. We used the following tests in our bivariate analysis:

1. *Chi-square test of independence* (both nominal variables): to determine if there is an association between our nominal variable, *participation in internships*, and another nominal variable. The null hypothesis for the test assumes there is no association between the two variables. For example, to understand if *participation in internships* is associated with *gender*, we conducted this test. We further describe the strength of our associations by reporting Cramer's V coefficient (range 0-1) for our statistically significant results. Cohen suggested that the magnitude of effect size for Cramer's V can belong to three categories: small=0.10, medium=0.30, and large=0.50 [35].

2. *Two samples Mann–Whitney U two-tailed test* (one nominal, one ordinal/interval): to assess if the samples of an ordinal/interval variable of interest for our two groups came from similar or different populations. The test has the null hypothesis that the distribution of both population distributions is similar. For example, this test was used to determine if the distribution of students' *household income* for our two groups, students who interned and those who did not, came from similar or different populations of CS undergraduate students. We further describe the effect size reporting eta square (η^2) [34, 56].

Quantitative Multivariate Analysis. For RQ.4 (What are the factors that influence undergraduate computing students' participation in internships?), we used a binary logistic regression model to identify consequential factors for securing internships. This model can be used to understand the relationship between categorical (e.g., Gender) and continuous (e.g., GPA) explanatory variable(s) and a dichotomous categorical (internship participation: yes/no) response variable [56]. The logit (i.e., the natural logarithm of an odds ratio, a measure that defines the ratio of successes to failures for an event) forms the basis of logistic regression. The odds ratio provides a measure that represents the odds that an outcome will occur (e.g., a student participates in an internship), given the presence of some other factor and controlling for other predictors. For example, we can obtain an odds ratio of a student's participation in an internship given they took high school courses in CS. This measure helps us quantify the strength of the correlation between demographic, academic, and identity factors and a student's participation in an internship(s). The logistic regression equation takes the following form:

$$Z = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{12} X_{12}$$

where, P_i is the probability of event i, β_0 is the constant coefficient, $X_1 \ldots X_{12}$ are the explanatory variables, and $\beta_1 \ldots \beta_{12}$ are coefficients of explanatory variables. A positive coefficient indicates a positive correlation between response variable and the coefficient's respective explanatory variable, and a negative coefficient indicates a negative correlation. For a logistic regression model, the null and alternative hypotheses are:

$$H_0 = \beta_1 = \beta_2 = \cdots = \beta_{12} = 0$$

$$H_A = \beta_1 = \beta_2 = \cdots = \beta_{12} \neq 0$$

In our model, we incorporate 12 explanatory variables after getting rid of one of the explanatory variables, age, due to multicollinearity (as described in Section 4.3.6). Therefore, our null hypothesis, $\boldsymbol{H_0}$ is: *None of the* *predictor variables in our model have a relationship with computing students' participation in internships*. The alternative hypothesis, $\boldsymbol{H_A}$ is *at least one of the predictor variables in our model significantly contributes to CS students' probability of participating in internships*. For our regression analysis, we treated ordinal explanatory variables (e.g., year in school) as continuous similar to other research in social sciences [133]. Our analysis including data cleaning and preprocessing was conducted in Microsoft Excel, IBM SPSS, and Python libraries such as pandas, matplotlib, seaborn, and researchpy [154].

4.3.8 Authors' positionality

Regarding our positioning to internships, I pursued an internship during their CS graduate school and have worked for multiple years in the tech industry after graduation. Dr. Gardner-McCune pursued four internships during their undergraduate and graduate CS program. Both of us believe that pursuing internships have value in gaining employment and to secure an internship, one needs to take active steps outside of coursework. Our position might have influenced the qualitative coding process.

4.4 Findings/Results

4.4.1 Who participates in internships and preparation practices (RQ1 and RQ2 as reported in Paper 1, Kapoor & Gardner-McCune (SIGCSE 2020))

In this section, we will answer our first two research questions of our second study. These questions are:

> **RQ1.** Who are the computing undergraduate students that participate in industry internships?
>
> **RQ2.** How does the preparation process of computing undergraduate students who secure an internship differ from those who do not intern?

Of the 536 students in our sample for Paper 1, 40.1% of the students (n=215) interned during their undergraduate studies or were hired into internships in the summer following the study for the first time. Specifically, 22.9% of the 536 students interned previously (n=123) and 17.2% of the 536 students were interning the summer following the study for the first time (n=92). The other 59.9% specified that they had never interned (n=321). 37.7% students at Site A (n=183), 56.8% students at Site B (n=25) and 100% students at Site C (n=7) secured an internship. In our analysis, we only consider internship participation during the 4+ years in CS degree programs. The internships ranged from working at local companies or startups such as Gainesville Regional Utilities and Airbnb to established corporations like Google and Amazon. The roles in which the students interned were eclectic and spanned various subdisciplines of computing including software engineering, user experience design, and data science.

4.4.1.1 Influence of demographics on participation in internships (RQ1)

We analyzed student responses across five demographic variables and a variable, *Participation in Internships*, with two levels, 'Yes' and 'No'. The former level consisted of students who interned or who were interning the summer following our study. Our five demographic variables were: *Gender, Race/Ethnicity, Academic standing, Household (family) income,* and *Employment status.* These factors helped us in answering *RQ1. Who are the CS undergraduate students that participate in industry internships?* We report our findings through a graphical representation of the demographics (Figure 2) and tabular representation of the statistical results (Table 11).

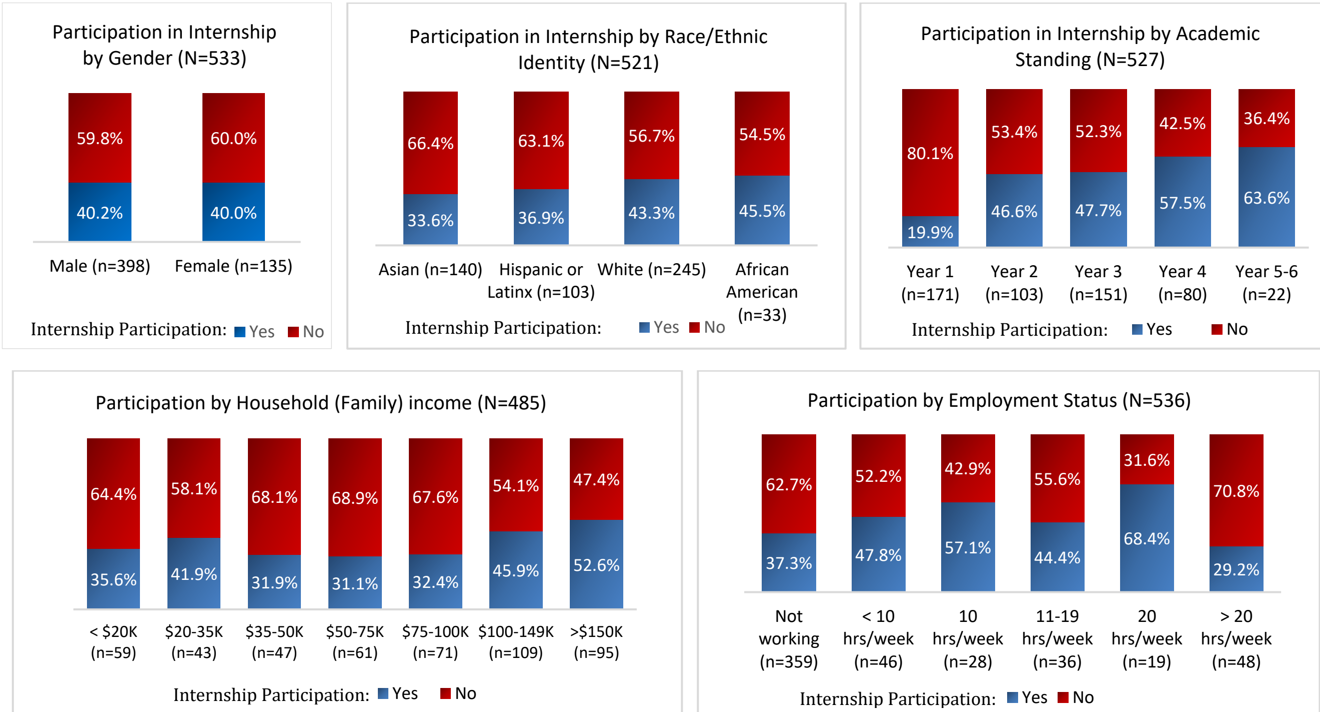

Figure 2. Demographics of Students who participate and do not participate in Internship as reported in Kapoor & Gardner-McCune (SIGCSE 2020)

Table 11. Statistical Tests for Participation in Internship as reported in Kapoor & Gardner-McCune (SIGCSE 2020)

	Statistical Significance			**Effect Size**
Demographic*	**χ^2**	**df**	**p-value**	**Cramer's V**
Gender (N=533)	0.00#	1	1.000	0.002
Race/Ethnicity (N=521)	4.29	3	0.230	0.091
Demographic	**z**		**p-value**	**η^2**
Academic standing (N=527)	-6.63		**0.000**	0.083
Household income (N=485)	-2.76		**0.006**	0.016
Employment Status (N=536)	-1.46		0.140	0.004
*marginal group omitted for small numbers. #continuity correction for 2x2 tables.				

We found that participation in an internship did not differ significantly by Gender (see Figure 2 and Table 11). Thus, we fail to reject the null hypothesis that participation in internships is not associated with Gender. Regarding Race/Ethnicity, 45.5% of the 33 African Americans students and 43.3% of the 245 White students reported that they interned, which were higher than the total number of students who interned (40.1%). 36.9% of the 103 Hispanic or Latinx students and 33.6% of the 140 Asian students interned, which were lower than the aggregated number of interns across our sample. **The results across racial/ethnic identity were also not statistically significant (Table 11).**

The percentage of students who participated in at least one internship or were interning the summer following the study increased across academic standing in our sample. 19.9% of the freshmen interned/were interning the following summer compared to 46.6% sophomores, 47.7% juniors, 57.5% seniors, and 63.6% Year 5-6 students. The results were statistically significant when conducting the Mann Whitney U test ($z = -6.63$, $p<0.001$). η^2, a measure for the strength of association, was found to be 0.083 which is categorized as a medium effect by

Cohen [35]. **For Household (family) income, which is a metric commonly used for socioeconomic status, we observed that students who reported higher Household income were more likely to pursue internships compared to those who had a lower Household income (Figure 2).** Further, participation in internships across reported Household income was statistically significant (α=0.5) when conducting Mann Whitney U test ($z = -2.76$, $p = 0.006$). Effect size (η^2) was found to be 0.016 which is categorized as a small effect by Cohen [6, 32].

Finally, for our last demographic variable, Employment status, we saw that two-thirds of students in our sample (359 of 536 students) reported that they do not work along with their degree program while the other one third of students in our sample worked anywhere from less than 10 hours/week to greater than 20 hours/week. While we noticed that those who were not working or were working for more than 20 hours per week were less likely to participate in internships, **based on disaggregation of our dataset using Employment status, the results were not significant** when conducting the Mann Whitney U test.

To sum up, we found that higher household income and higher academic standing (e.g., junior or senior) positively correlated with internship participation. As a corollary, lower household income and lower academic standing (e.g., freshman or sophomore) were less likely to participate in internships. Additionally, participation in internships were not significantly associated with gender, employment status, and racial/ethnic identity.

4.4.1.2 Students' preparation process to secure internships (RQ2)

Our second research question focused on analyzing the differences between students who intern and those who do not through the lens of their preparation and participation in the application process. 486 students responded to a question in our survey: "How did you prepare or how are you preparing to get an internship?". We used thematic analysis to code their responses which led to 893 codes, 72 unique codes, and seven categories. Four themes emerged from these categories that describe the students' preparation process. We first describe these themes and then compare the students who interned and those who did not within each theme. We also use quantitative data from our survey to explore and triangulate the relationships between our qualitative findings and quantitative results.

Theme 1: Engagement in the application process. 45.7% of the 486 student responses that fell in this theme (n=222) described how students were preparing for internships or previously secured an internship position by actively engaging in the application process. They created resumes or cover letters, reported the application avenues which included online applications or attending career fairs, and stated strategies they are using to secure an internship position. These strategies included applying early, applying to a large number of companies, networking with employers, dedicating specific time along with coursework for career preparation, taking advantage of connections (e.g. family), speaking to employers who were less desirable to develop interview skills, taking unpaid internships to gain experience, using a well-developed LinkedIn profile to contact recruiters, researching a company before applying, and receiving mentorship from seniors, family, university career centers, or peers who secured internships. For instance, Student P368, a senior female who had previously interned stated, "*Since freshman year, I have been very career-focused. I have attended career showcase & CDW [Career Development Workshop which is equivalent to a career fair where employers recruit candidates] every semester. Furthermore, before my first internship, I attended workshops and visited the Career Resources Center several times before I felt prepared (resume & interview-wise) for employment*."

Theme 2: Skill building. Within this theme, 44.9% of the 486 students (n=218) described that they are building technical and professional skills by getting involved outside of coursework to prepare for securing an internship position. The involvement outside of coursework covered a variety of activities or avenues including personal projects, clubs/student organizations, conferences, game jams, hackathons, team projects, study abroad programs, ethical hacking, boot camps, certifications, research labs, online courses, and gaining leadership experiences. Students stated that they are developing technical skills such as learning programming languages and web frameworks; social skills; professional skills such as communication and networking; and interviewing skills by participating in avenues outside of coursework. Seven students also reported that they were taking useful courses to build technical skills and secure an internship. Students were developing these skills for three reasons: to explore computing disciplines, show employers their involvement, and to gain competencies in a specific skill due to self-interest. For example, Student P239, a senior male who had interned suggested, "*I've been preparing since late 2017 by attending UFSIT [cyber security] club meetings, taking cybersecurity classes, participating in ethical hacking events*."

Theme 3: Explicit interview preparation. In this theme, 27.4% of the 486 students (n=133) stated that they secured an internship or are preparing to secure an internship by practicing technical interview programming problems on websites like LeetCode [170], GeeksforGeeks [171], and HackerRank [172], developing interviewing skills, studying data structures and algorithms, and reading books of which "Cracking the Coding Interview" [98] was the most prominent. Students reported they started using these resources after previous unsuccessful experiences in securing an internship position, or suggestions from recruiters, friends, or previous interns. Student P426, a junior female who interned stated that she "*read books such as Cracking the Coding Interview, practiced LeetCode problems online, and worked through a couple of problems with friends. [She] went to resume reviews hosted by a club [she is] active with and went to information sessions on campus to find opportunities*."

Theme 4: Status quo: relying on coursework or no preparation. In our final theme, 23% of the 486 students (n=112) reported that they were not preparing for internship positions, rather they were relying on coursework to prepare them for interviews, or wanted to focus on securing a good GPA which they believed would lead to a subsequent internship position. Students also stated in this theme that they were not preparing due to lack of interest or for not having time to manage the preparation process with coursework. For instance, Student P154, a sophomore male who had not interned before stated that he is "*making sure [his] grades are impressive and taking as much away (e.g. skills and knowledge) from [his] classes as possible*" to prepare for the internship recruitment process.

Comparing the preparation process. When comparing the preparation process of interns and students who did not pursue internships, we found that a higher percentage of interns (36.8% of the 190 students, n=70) belonged to the Explicit Interview Preparation theme when compared to students who did not intern (21.3% of the 296 students, n=63) - a difference of 15.5 percentage points, χ^2 (1, N = 486) = 14.09, $p < 0.001$. This finding is corroborated by two quantitative questions we asked in our survey. The first question focused on the time CS students devote to career development and the second asked their involvement in practicing technical interview questions. **We found that the median number of hours that the interns spent on career preparation outside of coursework were two to three hours per week compared to one hour per week by students who do not intern.** The group differences were statistically significant when we conducted the Mann Whitney U test ($z = -4.40$, $p < 0.001$, $\eta^2 = 0.04$). The effect size was 0.04, which is categorized as a small to medium effect by Cohen [35]. The second quantitative question, students' involvement in practicing technical interview questions was also significant when we conducted the Mann Whitney U test ($z = -8.57$, $p < 0.001$, $\eta^2 = 0.14$). The effect size was 0.14

which is categorized as a large effect [35]. **We observed that those who regularly practiced or were familiar with technical interview questions on platforms such as LeetCode and HackerRank were three times as likely to secure an internship, compared with those who never practiced them - a percentage difference of 44.7 percentage points (see Figure 3).**

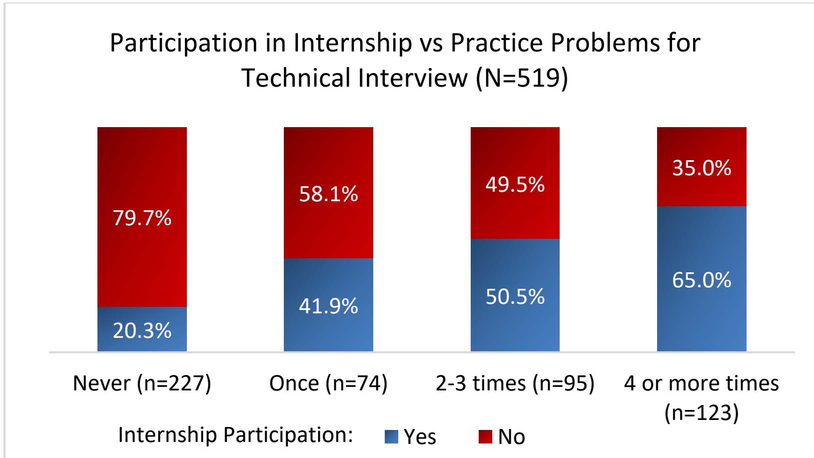

Figure 3. Practicing technical interview problems as reported in Kapoor & Gardner-McCune (SIGCSE 2020)

For the *Status-quo* theme, we found more students who did not intern (28.7%) compared to the students who interned (14.2%): χ^2 (1, N = 486) = 13.73, p < 0.001. **Thus, students who did not intern were relying on coursework, focusing on getting a high GPA to secure an internship, or were not preparing for internships.** We examined whether GPA is a factor to secure internships, but the results were not statistically significant when conducting the Mann Whitney U test (z = -0.29, p = 0.77, N = 504) indicating that academically the average GPA of an intern and a student who did not participate in an internship were similar. The mean GPA for students who interned was 3.47 compared to 3.44 for the students who did not intern. We conducted the Mann Whitney U test instead of an independent samples t-test as the GPA data did not follow the normal distribution. We also conducted an in-depth analysis of why the students were not preparing to secure internships and report our findings in the next subsection.

Finally, the students who interned (51.6% of the 190, n=98) were more likely to engage in the application process when compared to students who did not intern (41.9% of the 296, n=124). The results were statistically significant, χ^2 (1, N = 486) = 4.38, p = 0.036. Responses falling in the Skill Building theme were independent of students' participation in internships, which means that students' mentioning that they were working on building skills was not correlated with their participation in an internship. In the future, it would be valuable to understand the nuances in skill building - such as what skills are acquired by students and from where? How much effort is exerted by students in skill acquisition? If skill building leads their identity status shift from exploration to commitment phases [96]?

4.4.2 Barriers to participation (RQ3 as reported in Paper 2, Kapoor & Gardner-McCune (ACE 2020))

Our second paper, Kapoor & Gardner-McCune (ACE 2020), focused on understanding why most students in our sample (59.9% of 533 students) are not participating in internships (RQ3. *What barriers do CS undergraduate students, who do not intern, encounter in securing an industry internship?*). To answer this research question, we analyzed student responses to an open-ended question in the survey, "*Why haven't you interned so far?*". We used thematic analysis and coded student responses into 434 primary codes, 70 unique codes, and 18 categories. Four themes emerged from these categories (see Table 12 and Figure 4).

Table 12. Themes for Barriers to Securing Internships (N=302) as reported in Kapoor & Gardner-McCune (ACE 2020)

Themes	Count (n)	Percentage
Low self-efficacy	149	49.3%
Actions	113	37.4%
Alternate priority	102	33.8%
Application process challenges	16	5.3%

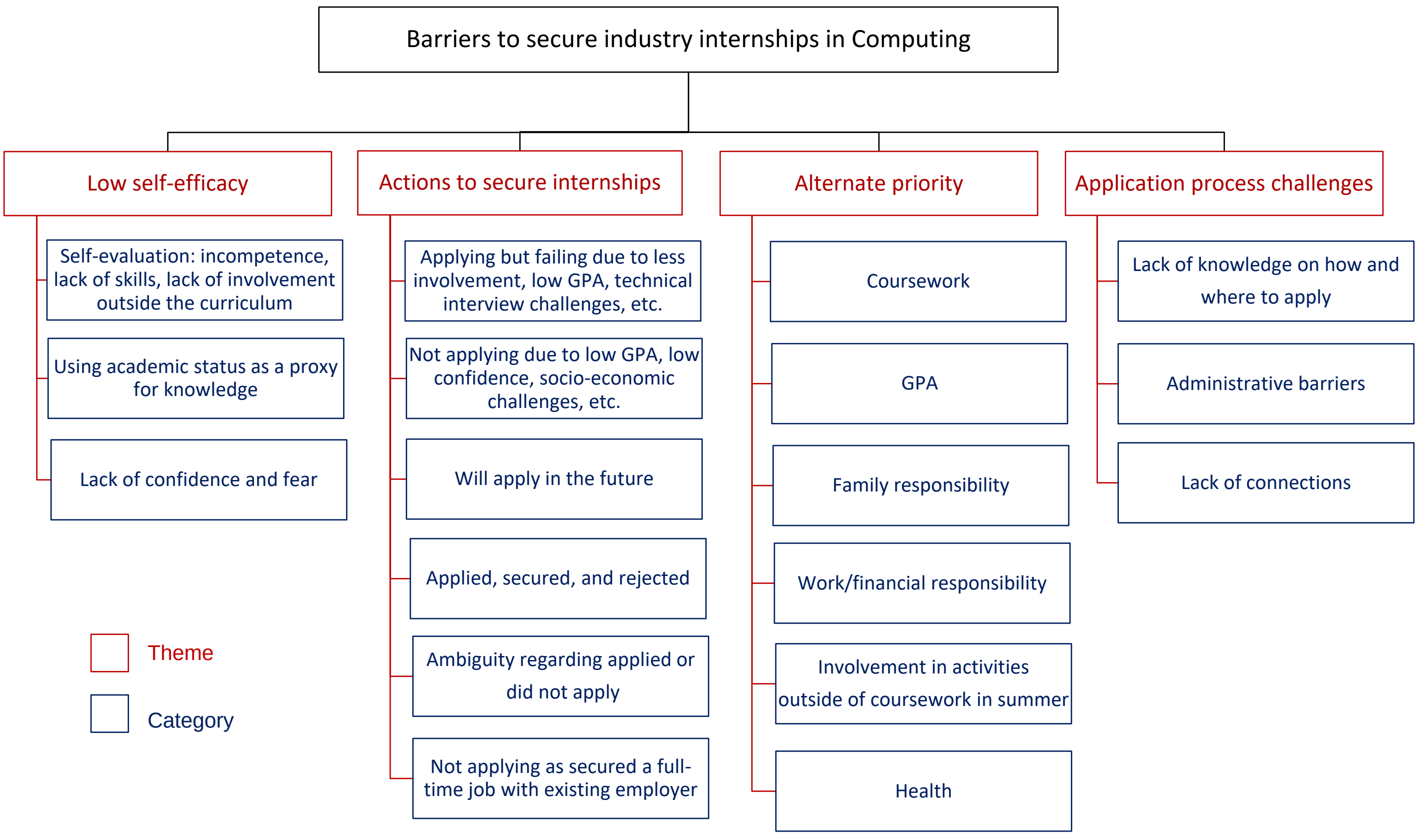

Figure 4. Thematic Analysis of Barriers to Securing Internships in Computing as reported in Kapoor & Gardner-McCune (ACE 2020)

Theme 1: Low self-efficacy. In this theme, 49% of the 302 CS undergraduate students who did not intern (n=149) described that they were either not applying for internships or were not securing applied positions due to properties related to self-efficacy. These properties fell into three broad categories: self-evaluation (n=85), academic status (n=71), and lack of confidence and fear (n=19).

Eighty-five students in the self-evaluation category gauged their technical competence and stated that they did not have the necessary skills, were incompetent, lacked skills they thought were sought by the industry professionals or lacked involvement in personal projects, technical interview challenges, or activities outside of coursework. Students also evaluated their competence by assessing if they had taken appropriate coursework such as "*Data Structures and Algorithms*" or if they have the necessary competencies for a specific internship position in a CS subdiscipline.

Further, students who belonged to the academic status category, reported that they were not applying or securing an internship because of their age or year the students were in their degree program, student status in their program such as transfer or part-time student, or low GPA. Such students specified they were "*freshman*", "*sophomore*", "*transfer student*", "*young*", "*new learner*", etc. These students used their academic status as a proxy for gauging their competence to secure an internship position.

In addition, 19 students said that they lacked personal dispositional traits such as "*confidence*" or "*motivation*" to secure an internship or were "*intimidated*" to apply for a position. The quotes in this category were classified based on a participant's feelings. The latter students were coded into a lack of confidence and fear category. Some representative quotes from students belonging to this theme and different categories on why they did not intern include (Note that participant quotes can belong to more than one theme):

Self-evaluation: lack of experience and skills (Category 1.1)

"I haven't interned yet because I'm too inexperienced to actually be competent at anything that I do, I'm still trying to transition my skills acquired in the classroom to the real world and currently I suck at that if I'm not given some form of direction or some type of hint at what I should do or how I should go about it." - P301, Freshman Male

"I feel like I don't have the skills required to intern, and my resume is not great." - P204, Sophomore Male

"*Not enough experience or intriguing personal projects; Lack of experience, work-wise and coding-wise*. - P376, Senior Male

"*I'm not good enough to qualify*." - P341, Senior Female

Academic status: a proxy for gauging competence (Category 1.2)

"I am a freshman meaning recruiters don't consider me a serious applicant until I'm a sophomore and have taken important classes like Data structures and computer organization." - P156, Freshman Male

"I am not very far in the computer science major yet and I have not gone seeking out internships." -P287, Sophomore Female

"I came from a community college where we learned our theoretical classes first, which is not desirable for most companies. Within a semester or two I will have the desired classes they want. I also lack technical experience via projects and club involvement." - P162, Junior Female

Lack of confidence and fear (Category 1.3)

"I'm not sure how to begin finding an internship and I have a lot of anxiety and feel incompetent." - P327, Junior Female

"Anxiety about following through with smaller companies and a fear of rejection by putting myself out to a large number of internships." - P241, Senior Male

When we disaggregated the demographics of the students to understand if low self-efficacy was dependent on gender and if low self-efficacy was a concern only for CS students in preliminary years of their academic degree program, **we found that on average females were higher in the low self-efficacy theme compared to males. 58% of the 77 females (n=45) who did not intern belonged to this theme compared to 46% of the 223 males (n=103).** Specifically for the three categories, females were higher in each category: 35% of the 77 females (n=27) in self-evaluation compared to 26% of the 223 males (n=58); 31% of the 77 females (n=24) in academic status compared to 21% of the 223 males (n=46); and 8% of the 77 females (n=6) in confidence and fear compared to 6% of the 223 males (n=13). While the freshmen who did not intern were most prominent in our sample in the self-efficacy theme (68% of 130, n=88), it is a cause of concern that a large number of sophomores (33% of 52, n=17), juniors (37% of 70, n=26), and seniors (29% of 34, n=10) who did not intern also had low self-efficacy.

Theme 2: Actions to secure internships. Within this theme, 37% of the 302 CS undergraduate students who did not intern (n=113) described their actions to secure internship positions in six broad categories: applied but failed, did not apply, will apply in future, ambiguity on intent to apply, applied-secured-and-declined, and not applying because of secured full-time employment.

Of the 113 students, 42% described that they applied and did not succeed (n=47). Students who applied but failed to secure a position attributed their failure to lack of involvement outside of the classroom in extra-curricular activities, low confidence, low GPA, less experience when compared to peers, and challenges related to coding they faced during the technical interview process. In contrast, 27% of the 113 students (n=31) reported explicitly that they were not applying because of low confidence, low GPA, focus on coursework and alternate responsibilities like work, family, or other socio-economic challenges. Further, 16% of the 113 students (n=18) stated that they were working on building skills and will apply in the future and 12% had ambiguous responses regarding whether or not they were applying for internships (n=13). In the latter category, a student responded by stating that they "*have not had an opportunity*". In addition, 4% of these 113 students who did not intern (n=5) received an offer but declined an internship position due to low offered stipend, shifting priorities like starting their own company, or stating that the offered position was not related to computing. Two students did not apply for internships as they had secured pathways to full-time employment through their part-time work and planned to join their part-time employer after graduating. Equal proportions of males and females were not applying for internships in our sample. Representative quotes from students belonging to this theme on why they did not intern include:

Applied but failed (Category 2.1)

Prominent barriers in this category: Lack of involvement outside of classroom in extra-curricular activities, low confidence, low GPA, and technical interview challenges

"Recruiters that I have talked to have said to work on side projects. Companies that I have applied online to have all rejected my application." - P250, Sophomore Male

"The internship process is difficult. I applied and interviewed with multiple companies but I didn't do great on the technical interview side because I didn't take Data Structures course yet, although I taught myself some Data Structures it didn't help that much due to my lack of deep understanding." -P673, Junior Male

"Because they are others out there with better experience for the internships that I am trying to apply for. I applied to over 15 internship opportunities but did not get beyond the first line in all of them."- P320, Senior Male

"No offered yet thus far. I have only participated in one career showcase [career fair] and my current GPA is not pleasing." - P401, Year 5-6 Female

Did not apply (Category 2.2)

Prominent barriers in this category: coursework, low GPA, low confidence, socio-economic challenges like finance and family

"I have not actively searched for an internship yet. I also do not feel I am ready for one yet." -P167, Freshman Female

"Haven't applied to many big companies that hire a lot of people. Also have been busy taking classes."- P177, Junior Female

"I haven't applied, I had a job to support my living and school expenses and leaving for an internship would have been too much strain on me. I support myself, so I couldn't lean on my parents financials."-P183, Senior Male

Will apply in future (Category 2.3)

"I had to take classes, and thus have no time to allocate for one as of now. In addition, I am trying to spend my freshman and sophomore years building experience. I plan on getting an internship after my Junior year when I have solidified my professional and technical experience." - P344, Sophomore Female

Applied, secured, and declined (Category 2.4)

Prominent barriers in this category: financial constraints and alternate interests

"I declined my internships because I want to work on my own startup." – P630, Sophomore Male

"I am a non-traditional student with a family and cannot afford to take an internship when I instead need long-term employment. I wanted to focus on my school and graduate quickly so that I could support my family. I actually interviewed for and was accepted for a Summer 2019 internship, but I could not afford to travel to Tampa and support my family with the offered compensation."- P600, Senior Female

Theme 3: Alternate priority. In this theme, 34% of the 302 CS undergraduate students (n=102) described they had not interned as they were focusing on coursework or improving their GPA (n=67), managing responsibilities revolving around work or family (n=26), or were involved in other activities over summer including study abroad (n=6), research (n=4), relaxation (n=2), startup (n=1), and personal project (n=1). The students who focused on coursework or improving their GPA wanted to build technical and professional competencies through the curriculum, planned to graduate early, or had a hard time managing coursework and extra-curricular activities. In addition, two students described that they did not intern because of medical conditions or health problems. Students also explained they had difficulties in managing time for multiple activities or wanted to focus on coursework during summer for graduating early. Some representative quotes in this theme included:

Focus on coursework and GPA (Category 3.1 and 3.2)

"I have been busy trying to keep my grades up for all of my classes, and I have found I am having difficulty with some; I am afraid that an extra workload in the form of an internship would bring my GPA to a dangerous low." - P243 Freshman Female

"I wanted to get further along with my courses and leave my internship for my last semester, this would allow me to hopefully transition into a job easier." - P364, Junior Male

Family, work, and financial responsibilities (Category 3.3 and 3.4)

"I haven't had the time since I have a job and classes, and I don't think I'm far enough into the major to be able to take on an internship." - P654, Sophomore Female

"I have a full-time job, taking CS one or two courses at a time to be able to balance. I've also been moving for my job." - P563 Junior Female

"Classes consume a lot of my time, my family's financial situation is also dire, and I more or less don't have the money to pay for housing elsewhere." - P397, Junior Male

"Due to financial issues, I have had to study and work at the same time and have not had as much time to reach out for internships." - P248, Senior Male

Involvement in activities over summer: study abroad, research, projects, etc. (Category 3.5)

"I am still in my first year of college and opted to take summer classes and do on Campus research my first summer to learn more before applying to jobs." - P221 Freshman Male

"I have not looked to obtain one yet. I have studied abroad instead." - P275 Sophomore Male

"I did not get a lot out of the Career Development Workshop/Career Showcase [career fair] this year and I am studying abroad in Hong Kong this summer instead." - P409 Sophomore Female

"I have not had the time as I've been busying myself with extracurriculars that I have used to enjoy my college experience." - P434 Junior Female

Health concerns (Category 3.6)

"For a few years it was lack of experience. In recent years I've felt more qualified, but I've dealt with a lot of health problems, and taking care of my health consumes a lot of free time that should be allocated to professional development." - P231, Senior Male

We also observed in this theme that females were more likely to be focused on coursework (30% of 77 females, n=23) when compared to males (19% of 223 males, n=43), while males were more likely to manage responsibilities revolving around work or family with coursework (10% of 223 males, n=22) when compared to females (5% of 77 females, n=4).

Theme 4: Application process challenges. 5% of the 302 CS undergraduate students who did not intern (n=16) described that they had limited knowledge of how and where to apply for internship positions, lacked connections to apply for internships, or had visa restrictions that hindered them from participating in internships. Survey respondents like, P465, a male freshman who doesn't "*know where to find internship opportunities*" or P541, a male freshman who did not intern "*mainly due to a lack of connections*" fell in this theme. Other representative quotes of students belonging to this theme on why they did not intern include,

Lack of knowledge on how and where to apply (Category 4.1)

"*I am having difficulties with my academics and do not know how to find one.*" - P246, Freshman Male

"I find it hard to find a company that will give me an internship in something I am interested in such as cybersecurity." - P591 Sophomore Male

"Haven't had relevant coursework or found employers willing to take interns with less than the usual required classes." - P284 Junior Male

Administrative barriers (Category 4.2)

"I have not interned so far because my status with the United States does not allow me to obtain a job."- P129 Freshman Female

Thus, we found that the barriers faced by students who do not intern include low self-efficacy to apply or secure an internship position, less agency to apply for internship positions, focus on alternate priorities including coursework, family/work/financial responsibilities, or challenges related to the application process.

4.4.3 Factors influencing participation (RQ4 as reported in Paper 3, Wolf et al. (SIGCSE 2023))

Our third paper, Wolf et al. (SIGCSE 2023) aimed to answer the following RQ4. *What are the factors that influence undergraduate computing students' participation in internships?* To answer this question, we analyzed data from 518 undergraduate students in computing majors enrolled at a single institution in the US. Trends in our explanatory variables and response variables are described in Tables 13, 14, and 15.

Table 13: Descriptive Statistics of Dependent/Response Variable as reported in Wolf et al. (SIGCSE 2023)

Variable (N=518)	Outcome	Count	%
Internship participation	No internship experience	301	58.1
	Participated in at least 1 internship	217	41.9

Table 14: Descriptive Statistics of Explanatory Ordinal/Numeric Variables as reported in Wolf et al. (SIGCSE 2023)

Variable (N=518)	Mean	SD	SE	95% Conf. Interval	
GPA	3.45	0.42	0.02	3.42	3.49
Achievement score	20.09	3.58	0.16	19.78	20.40
Diffusion score	15.54	4.02	0.18	15.20	15.89
Foreclosure score	11.44	4.04	0.18	11.09	11.79
Moratorium score	20.53	3.65	0.16	20.22	20.85
Involvement score	10.25	6.51	0.29	9.69	10.81
Household income	4.82	1.89	0.08	4.66	4.98
Year in school	2.54	1.20	0.05	2.44	2.65

Table 15: Descriptive Statistics of Explanatory Categorical Variables as reported in Wolf et al. (SIGCSE 2023)

Variable (N=518)	Outcome	Count	Percent
Secondary CS Education (High school CS courses)	No	261	50.39
	Yes	257	49.61
Employment status	Unemployed	360	69.50
	Employed	158	30.50
Gender	Male	379	73.17
	Female	139	26.83
Race	White or Asian	374	72.20
	Underrepresented	144	27.80

Our regression results can be found in Table 16 and our model is significant ($p < 0.001$). In this table, Coef. β represents the regression coefficient which estimates the relationship between the individual factor and whether students have received an internship. Std. Err represents the standard error, which measures the precision of the estimate of the coefficient. Z represents the Z-value, which is a test statistic that measures the ratio between a coefficient and the standard error. The Z-value is used to calculate the p-value of a factor, which is represented by $p > |z|$. A p-value is used to determine if a factor is statistically significant ($p < 0.05$). The odds ratio is a measure of practical significance and is represented by exp(β). If the odds ratio is greater than 1, the event that a student participates in an internship is more likely to occur as the predictor value increases. The last two columns represent the confidence intervals, which show the range of values that the Odds Ratio could fall under with 95% confidence.

Table 16: Regression Results as reported in Wolf et al. (SIGCSE 2023)

	Coef. β	Std. Err	Z	p > |Z|	CI for Coef. β [0.025	CI for Coef. β 0.975]	Odds Ratio exp(β)	CI for Odds Ratio 5%	CI for Odds Ratio 95%
Const	-5.53	1.60	-3.45	0.00	-8.67	-2.39	0.00	0.00	0.09
HS CS Edu.	0.29	0.21	1.36	0.18	-0.13	0.71	1.34	0.88	2.04
Employment	0.10	0.23	0.45	0.65	-0.35	0.56	1.11	0.70	1.75
Year in School	0.57	0.10	5.72	**0.00****	0.38	0.77	1.77	1.46	2.16
GPA	0.51	0.28	1.80	0.07	-0.05	1.06	1.66	0.96	2.89
Household Income	0.22	0.06	3.76	**0.00****	0.11	0.34	1.25	1.11	1.40
Gender	–0.28	0.24	-1.16	0.25	-0.76	0.19	0.75	0.47	1.22
Race	0.16	0.24	0.67	0.50	-0.31	0.63	1.18	0.73	1.88
Moratorium Score	0.01	0.03	0.48	0.64	-0.04	0.07	1.01	0.96	1.07
Diffusion Score	-0.06	0.03	-2.14	**0.03***	-0.12	-0.01	0.94	0.89	0.99
Achievement Score	0.01	0.03	0.29	0.77	-0.05	0.07	1.01	0.95	1.07
Foreclosure Score	-0.01	0.03	-0.34	0.74	-0.06	0.05	0.99	0.94	1.05
Involvement Score	0.12	0.02	6.79	**0.00****	0.09	0.16	1.13	1.09	1.17
No. of Observations: 518 Df Residuals: 505 Df Model: 12		Pseudo R^2: 0.21 Log-Likelihood: -279.5 LL-Null: -352.2				LLR p-value: 4.7e-25 * $p < 0.05$ ** $p < 0.001$			

According to our regression results, *year in school*, *household income*, *identity diffusion score*, and *external involvement score* are significant and are influential in predicting whether students will participate in internships. The odds ratio for the *year in school* indicates that for every one-year increase, a student is 1.77 times as likely to have participated in an internship, after controlling for other predictors. The odds ratio for *household income* indicates that for every one-unit increase (movement to the next socioeconomic status), a student is 1.25 times as likely to have participated in an internship (i.e., a one-unit increase in *household income* is associated with a 25% increase in the odds of a student participating in an internship). Similarly, the odds ratio for *external involvement* indicates that for every one unit increase in the external involvement score, a student is 1.13 times as likely to have participated in an internship. The odds ratio for *identity diffusion score* indicates that for every one unit increase in diffusion score, the odds of *not* securing an internship increases by a factor of 1.06 after controlling for other predictors [56].

Our model fit was evaluated using McFadden's pseudo-R^2 coefficient (ρ^2). **The pseudo-R^2 of 0.21 indicates an excellent model fit.** The values for pseudo-R^2 tend to be significantly lower than the standard R^2 and should not be interpreted by the same standards of fit as OLS regression. According to McFadden, "*values of .2 to .4 for ρ^2 represent an excellent fit*" [99].

4.5 Discussion and Conclusions

4.5.1 Internship participation and students' preparation process (RQ1 and RQ2)

We found that 40% of computing students in our sample participated in one or more internships. 57.5% of the CS students who were in their senior year participated in an internship. The percentage is similar to a national survey across different majors which found 61% of the students interned before graduation [109]. We also found that students belonging to lower socioeconomic status were significantly less likely to intern when compared with those who had higher socioeconomic status. Regarding CS students' preparation process for securing an internship, we found students who interned were more likely to be engaged in the application process and were using technical interview preparation websites more often when compared with students who do not intern. Similar to the study by McCartney and Sanders [97], students stated the importance of reviewing Data Structures and Algorithms for the internship preparation process. Our students, however, were learning these skills through technical interview preparation on online interview preparation websites in addition to coursework. We also found that students are building professional and technical skills through their involvement in informal activities such as hackathons and projects. These avenues provided students an opportunity to develop the skills which employers report are deficient in recent CS graduates [20, 130, 131].

Within the context of Bandura's properties for human agency [8], we observed that interns were more likely to be intentional in their approaches regarding the application process as they used strategies such as networking, applying through career fairs, and devoting time for career preparation outside of coursework. Interns were also highly self-reactive as they participated in activities for professional development and regulated their behavior after receiving advice from a mentor or peer. The students who did not intern were more likely to rely on coursework, were not preparing to secure internship positions or were spending minimal time on career preparation outside of coursework. These students were more likely to lack intentionality or forethought about industry expectations given that they relied on coursework or their high GPA for securing an internship. **Students who were not applying for internships also lacked the mechanisms to self-reflect as they were not participating in the job recruitment process. Interns, on the other hand, were self-reflecting on the ways to improve their ability to secure internships after failures in the interview process or after advice they received from the**

recruiters. To conclude, some students who were not interns lacked agentic resources that hindered their abilities to secure internships. This leads to a question: How can we prepare such students to participate in internships or other professional development activities so that they have the necessary skills to thrive in the job recruitment process?

4.5.2 Barriers to internship participation (RQ3)

Our work also contributes to the Computing Education literature understanding of the barriers that hinder computing undergraduate students' ability to secure industry internships. Four themes emerged related to these barriers: low self-efficacy, actions to secure internships, alternate priority, and application process challenges. We found that a majority of students who did not intern had low self-efficacy and they evaluated themselves as incompetent for securing an internship due to lack of technical skills, relevant experiences, or where they were in the degree program. There is a possibility that the students' evaluation of themselves as lacking technical skills is erroneous and based on misconceptions given that some students stated in the survey that companies do not hire interns until junior year, or companies require a high GPA from potential interns. These conceptions are not true given that our analysis from the same dataset as used in this paper has shown that 20% of the freshman and 45% of the sophomores pursued an internship [80]. Further, we have also found that there is no statistically significant difference in the GPA of students who intern and those who do not intern. Students who had less than a 3.0 GPA on a 4.0 scale also secured internships at top tech companies in the United States [80], thus contradicting these students' conceptions.

Further, computing undergraduate students also felt incompetent due to their academic status, which included the time they spent in the degree program or their experience in computing. They described lower confidence as well as fear of rejection which hindered them from even applying for positions. According to the Social Cognitive Career Theory (SCCT), these students lacked the necessary agency to form performance goals [89]. This performance goal of securing an industry internship is necessary to stretch a student's perceived ability and for attaining motivation to overcome obstacles that include applying to various companies for intern positions or preparing for the interviews.

The students who did not intern also had alternate priorities including coursework or work/family responsibilities that hindered their ability to secure or apply for an internship position. SCCT suggests that during the process of career exploration and skill development, students may face financial, cultural, or systematic obstacles or have varying levels of support from influential others. These obstacles may subsume students' agency thereby hindering the formation of performance goals that stretch the individual beyond their perceived abilities [89]. In accordance with SCCT, we observed in our data that some students may not adequately harness the process of skill development, experiential learning, and career exploration due to financial constraints, administrative constraints such as visas, academic constraints such as maintaining a GPA, social constraints including family responsibilities, psychological constraints such as low self-efficacy, and recruitment-process constraints which includes technical interview challenges or involvement in projects and extra-curricular activities. These constraints suggest that in addition to the course load in computing undergraduate curriculums, the industry expects student involvement outside the curriculum in terms of professional development and skill-building. Moreover, our students may face several other constraints outside of their academic life such as financial hardships that further exacerbate their ability for securing an internship. Leveraging financial capital to minimize these constraints by developing support programs for skill development and career exploration especially for such students might increase their competitiveness for joining the workforce or for securing an internship. Further, incorporating elements from other professional activities within the CS coursework can also reduce the burden on our students, especially for those students who do not attend informal activities such as clubs, thus increasing their ability for securing internships.

With regard to Bandura's properties for human agency: intentionality, forethought, self-reactiveness, and self-reflectiveness [8], the students who did not intern stated that they were not applying for internship positions, not preparing for securing internships as they had alternate priorities and felt academically incompetent due to their self-evaluation or where they were in their degree program. While some students were applying and not securing internships, others were not intentional in their approaches for securing internships, lacking the necessary forethought needed to secure an internship. Some students also relied on coursework or their high GPA for securing an internship, not knowing that active preparation is required outside the curriculum to secure a position. Students who are not applying for internships are losing an opportunity to improve professional and technical skills sought by the industry and for subsequently regulating their behavior to gain professional competence. Thus, such students lack the agentic resources necessary to thrive through the recruitment process.

4.5.3 Factors influencing students' participation in internships (RQ4)

The regression results in Paper 3 show that year in school, household income, external involvement score, and diffusion identity status score are significant predictors of internship participation in our model. Therefore, we reject the null hypothesis that there are no factors in our model that have a significant relationship with computing students' participation in internships. These results corroborate the findings in our bivariate analysis that factors outside the curriculum are at play that influences students' participation in internships. Our results also align with Hoekstra's study [65] which found age (correlated with the year in school) and participation in high-impact practices were significant predictors of securing internships in all majors. However, unlike Hoekstra's study, we did not find a relationship between race and gender and participation in internships in computing. This reduced disparity in computing could be because of strong labor markets and job opportunities in computing. Lastly, diffusion identity status seems to have a significant impact on internship participation. While higher exploration or higher commitment might not predict participation in an internship, a student in a lower commitment and lower exploration mode might face challenges in securing an internship. In the future, we would like to explore who are the students that are "stuck" in diffusion status. Are they freshmen or senior students? Finally, we would like to explore creating predictive machine-learning models for predicting students' participation in internships.

4.6 Recommendations

Recommendations for departments. We recommend departments to encourage students to pursue internships and disseminate the importance of pursuing internships. One way they can encourage students is by assisting student organizations and other professional development avenues which provide students with an opportunity for career exploration and developing technical or professional skills. Students who did not intern in our sample were either applying and not securing an internship or lacked agentic resources that hindered their ability to apply and secure internships. For the former students, we suggest the departments develop programs for improving technical competence and honing professional skills, while for the latter group, departments need to introduce programs for improving self-efficacy or for developing students' confidence. Additionally, programs must be designed so that students with alternate responsibilities, especially those of low socio-economic background, can understand the expectations of employment recruitment process and gain the skills required for securing internships within the curriculum. Without such support programs, SCCT suggests that regardless of a student's level of skills, talent, and interest, individuals will not have an opportunity to form strong self-efficacy and positive outcome beliefs [89]. Further, this hindrance to the students' career exploration and attainment process can lead them to doubt their competence or later join the workforce after graduation with an underprepared skillset. How will we satisfy the demand for computing graduates in such a scenario?

Recommendations for instructors. We suggest instructors and educators incorporate authentic skills required from the industry recruitment process within the curriculum so that all students can balance coursework with professional development and gain competencies in these skills. An example could be to use GitHub [173] for submitting projects so that students can show their portfolio to recruiters or using online code judges in Data Structures and Algorithms courses where students can practice the implementation of various data structures for technical interviews. This is necessary as computing students who have responsibilities outside of the classroom such as work have limited opportunities for participation in extracurricular activities at the university.

4.7 Limitations

Sample representation: Our findings represent a snapshot of the internship experiences taken from a sample of CS students at three US-based universities where participation in internships was optional. The results may or may not generalize to other majors, institutions, or geographic areas, especially to programs where participation in internships is mandatory before graduation. We provide a description of the research sites and leave it up to the readers to make appropriate inferences of our findings at similar types of institutions.

Moreover, our samples at Site B and Site C were relatively smaller than Site A. We did not offer students extra credit for participation at Site C and we collaborated with one instructor for extra-credit at Site B. The number of students at Site B and Site C who interned may not be representative of the population of students enrolled at the respective sites given the small sample and should be interpreted with caution. For instance, the number of students at Site B (57%) who interned were higher than those at Site A (40%). A larger sample size is required to understand the percentage of students who intern at Site B. However, the internships pursued by the students at both universities were actual real-world industry internships rather than interventions designed by academic-industry collaborations. Thus, student experiences in the real world strengthen external validity and our findings should generalize to CS undergraduate students who apply for internships in the industry in the United States. We also had a lower representation of certain groups such as Females and African Americans, but such groups were proportional to the respective proportions at the individual universities.

Data collection instrument: Data collected from survey-based research can induce response bias or interpretation of questions different from a researcher's intended meaning of a prompt. To mitigate this, we used insights from the analysis of our pilot study to reduce the interpretation bias of survey questions. In the future, we would additionally confirm or refute results from our survey analysis with data from interviews to strengthen the validity of our results from multiple data sources.

Qualitative inquiry: The coding process can be influenced by a researcher's biases and could have subjective interpretation. We attempt to validate our qualitative analysis through the transparency of our research process, using representative quotes from participants, and recognizing the researchers' positionality.

Quantitative analysis: Imputing missing data before running a model has a chance to increase the underestimation of standard errors and overestimation of test statistics [1]. Given that the overall missing data was relatively low (1.4%) when compared with the number of responses that had missing data (40%), we decided to impute data rather than discard responses. We report our data imputation technique for better transparency.

Our EOM-EIS identity scales had lower internal consistency due to the limited number of items used for each status. However, the Cronbach Alpha values were comparable to prior work. Additionally, we chose a logistic regression model for its simplicity, effectiveness, and lack of baselines. Prior work has observed that logistic regression produces somewhat comparable results as more advanced models in social sciences research [136]. However, our findings could be biased by the choice of our modeling technique and results from using other advanced models might yield different results.

Lastly, the model presented in this paper treats ordinally encoded variables like year in school and household income as continuous for simplicity. However, this method assumes linear effects between the intervals. These categorical variables may be better represented using one-hot encoding/dummy variables and dropping a column representative of a baseline. For example, we may assume that students are more likely to intern during the summer after their junior year compared to the summer after their freshman year (as students would have taken more advanced courses which are required for certain internships). If this is the case, the intervals are non-linear, and the continuous assumption of our model is naïve. In future iterations of this work, it may be of value to modify the ordinal representations using dummy variables for each of the categories and a baseline for year in school.

Inference: Our study is an observational study and results should not be interpreted as causal relationships.

4.8 Lessons Learned for Subsequent Studies

We found that a majority of computing students in our sample (60%) did not participate in internships. These students were less engaged in preparing to secure internships due to lack of agency or awareness of the recruitment process, had lower self-efficacy, and were impacted by alternate priorities such as financial, familial, or work responsibilities. Additionally, there is no known cohesive framework that provides researchers tools to investigate student participation in internships and answer the following question: What distinguishes a computing undergraduate student who has participated in several internships before graduation from those who have not participated in any internships? We also observed that the industry recruitment process for internships expects student involvement outside the already overloaded computing curriculum. Hence, we need to develop support programs to prepare our students for securing internships within the curriculum so that our students become more aware as well as gain the necessary skills they need for securing internships using a more equitable approach. In order to solve this problem and improve students’ awareness of the job recruitment process as well as prepare them for this process, we designed, implemented, and evaluated an intervention called “Hire Thy Gator Technical Interview Exercises”, which we will describe in the next Chapter.

5. Study 3: How can we improve our curriculum so that more students intern?

Given the importance of internships in computing (Chapter 3), it is concerning that only 40% students participate in internships across the undergraduate computing program (Chapter 4). Hence, we created a pedagogical intervention to prepare students for applying and securing internships by building their confidence. In this section, we elaborate on logistics and evaluation of our intervention called *Hire Thy Gator Technical Interview Exercises.* This study was conducted in Summer and Fall 2020, and the intervention was introduced in Fall 2020. Data from this study was published in the following conference proceedings between 2021-2023:

1. *Introducing a Technical Interview Preparation Activity in a Data Structures and Algorithms Course* at the ACM ITiCSE 2021 Conference in the Tips, Techniques, and Coursework Track (Short paper) [81]

2. *Implementation and Evaluation of Technical Interview Preparation Activities in a Data Structures and Algorithms Course* at the ACM SIGCSE TS 2023 Conference in the Experience Reports Track (Full paper) [84]

I was the lead author on both papers and Dr. Gardner-McCune was the supervisor and co-author. For the second paper, an undergraduate student researcher, Sajani Panchal was the second author and she helped on qualitative analysis as well as conducting a literature review in the area. In this section, we will use data and results from the above papers as well as analysis from an additional research question which we haven't published so far. The latter question (RQ1b, Section 5.7.2) investigates the efficacy of our intervention for different roles (students' participation as an interviewer vs interviewee).

5.1 Introduction

One role of computing degree programs is to educate individuals so they can contribute to the economy by joining the workforce. This goal aligns with the majority of computing students' aspirations to secure jobs in the industry after graduation [74]. Unfortunately, most undergraduates in a computing major have to devote career preparation time for technical interviews outside of coursework as these interviews act as gatekeepers to internships and full-time jobs in the technology industry [10, 72, 98, 143]. This need for time outside of the curriculum is unfavorable and inequitable, especially for students of low socioeconomic backgrounds who may not have substantial time outside of the curriculum due to family or work responsibilities [72]. In addition, students find these technical interviews as anxiety inducing and stressful [11]. To solve these issues, we introduced *Hire Thy Gator technical interview preparation activities* to familiarize students with the interview process and build students' confidence to succeed in these interviews.

In this section, we describe and evaluate the introduction of Hire Thy Gator technical interview preparation activities in a Data Structures and Algorithms (DSA) course. Our intervention included a panel on internship experiences, a role-play interview demonstration, two participatory mock interview preparation exercises where students interviewed each other first using self-selected peers and second through random pair-ups and graded short programming problems. The content of the technical interviews has a broad overlap with DSA courses [98] and hence our activities were introduced in this course. We will (1) explain the logistics and rationale for embedding these activities, (2) describe the lessons learned and evolution of the activities beyond the intervention semester, and (3) evaluate the impact of these activities on students. We report data from 257 students who participated in our intervention and 106 students who were a part of a control group. Students found that taking roles as an interviewer and interviewee increased their familiarity with the recruitment process, allowed them to self-evaluate their strengths and weaknesses, and prepared them for technical interviews.

Quantitatively, the intervention cohort that participated in our activities reported a higher average normalized confidence gain (0.42) than the control group (0.36) indicating that our activities can aid in building students' confidence. Our work contributes rich descriptions and preliminary evaluation of a scalable, collaborative, and formative professional development activity which can support students' awareness and preparation for future technical interviews as well as scaffold students' transition between coursework and technical interview preparation equitably.

5.2 Related Work

The hiring process in the US varies for roles which span eclectic computing areas such as software engineering, data science, user experience design, etc. Industry employers hire interns and full-time employees for these roles through a multi-stage competitive recruitment process [98, 143]. The process typically has three stages: an application phase, an interview phase, and a negotiation phase. During the application phase, an applicant applies to various roles and companies by submitting their resumes and answering questions on digital applications, career fairs, or company information sessions. The applications are screened, and candidates are selected for the next stage which is the interview phase based on a student's experience, GPA, and involvement in projects [143]. Companies invite applicants for one or more technical and behavioral interviews and there is variation in the number and rigor of the interviews depending on the job role and companies. A majority of companies ask students technical questions in an interview related to DSA, especially for software development and engineering positions. Finally, in the third stage, an offer is made by the company and the applicant has an opportunity to negotiate. Our intervention focuses on preparing students for the interviewing phase of software development and engineering jobs given their prominence and the overlap with our DSA course. Research on these technical interviews in computing industry spans three areas in literature:

5.2.1 Employer-centric research on structure and expectations in a technical interview

Work that explored expectations of employers in a technical interview includes Ford et. al's work [48] on interviewers' expectations from potential software engineer candidates. They found that interviewers were not only interested in the technical problem-solving ability of the candidates, but also the interpersonal skills such as effective communication skills. Another work assessing the structure of technical interviews by Stepanova et. al. [143] found that recruitment professionals reported differences in interview structure across companies with variations in components like coding tests, on-site interviews, team interviews, or behavioral interviews. However, it is evident from the aforementioned studies that technical interviews are used as a primary recruitment tool for securing jobs in the computing industry. Given that not all students have a considerable amount of time to prepare for these interviews outside the curriculum [72], we wanted to introduce an intervention that can provide preliminary exposure to technical interviews to our students.

5.2.2 Student-centric research on interview participation and factors that influence success

Studies have also explored student participation in technical interviews and factors that promote or hinder success in the interviews. This work includes Wyrich et al.'s study [160] which identified the individual characteristics of students' performance in solving coding challenges and found that students who completed coding challenges had higher grades, more programming experience, and higher happiness. Lunn et. al. [95] observed similar results and found that students who had more coding experience had positive experiences with technical interviews and a higher computing identity. Another example is Hall and Gosha's study [59] which identified African American students' participation in technical interviews and found that interview performance decreased with increasing anxiety and the anxiety decreased as students participated in more interviews. Other studies [11, 46] have also found that interviewees participating in technical interviews have experienced stress and anxiety which prohibits their performance. In short, these interviews can be stressful and higher participation may yield better outcomes. So why not use supplementary formative activities in coursework to help students feel more confident in their ability to excel in technical interviews? We aim to abate these issues through our activities.

5.2.3 Practitioner-centric research on designing interventions for interview preparation

A few interventions have been introduced in computing classrooms [46, 151] or through academic-industry partnered programs [2] which were intended to prepare students for technical interviews. These include Urness's work [151] on the introduction of technical coding exercises in a CS2 course in the form of programming assignments. However, this intervention focused on individual problem-solving akin to a coding test which is seldom a precursor to an actual technical interview [48]. Another work by Dillon et. al. [46] incorporated and evaluated the efficacy of the inclusion of coding exercises in CS2 and Object-Oriented Programming courses where students were assigned into groups of three and asked to think aloud and explain solutions using Zoom breakout rooms to their peers. They found that students received the activities positively but still showed adequate levels of anxiety. The latter intervention was introduced in a smaller course and the interview questions were provided by the instructor for the group. The setup did not consist of dyads with an interviewer and interviewee role. Our intervention is different from this intervention as we tried to mimic the more prevalent dyad interview format and we present how to scale our activities in large classrooms using a peer interview approach.

5.3 Settings

5.3.1 Educational institution

Our intervention was introduced in a DSA course at the University of Florida in the Fall 2020. At the research site, admission in undergraduate degree programs is competitive and participation in industry internship(s) before graduation is not mandatory. Our DSA course is a required course for CS and Computer Engineering majors and CS minors. It follows the CS1, CS2, and Discrete Mathematics courses and students have prior knowledge of programming in C++ and Java. 250-450 students enroll in the course in Spring and Fall and 100-150 in the Summer. For this study, we use data from 257 students who consented and participated in our intervention in Fall 2020 and 106 students who were enrolled in Summer 2020 in our course and did not participate in our activities (control group).

5.3.2 Course structure and content

Our course covers different DSA-related topics such as Algorithm Analysis, Sets, Maps, Trees, Graphs, Greedy Algorithms, etc. The language of instruction is C++, and the course has an equal mix of theory and practice. For the latter, students solve short programming DSA problems on a browser-based system and work on projects. The course was worth 4 credits in Summer and Fall 2020 and students had to attend three lectures led by the instructor and one discussion every week led by a peer mentor or teaching assistant. The course lasts 15 weeks in Fall and 12 weeks in Summer. In both Summer and Fall 2020, the course was online due to Covid-19, was taught by me, and followed a hybrid format structurally consisting of two remote synchronous lectures and discussion and two remote asynchronous pre-recorded lectures. Students were tested on a weekly quiz, two individual projects, a final ill-structured and self-proposed group project, and two exams in both semesters.

5.4 Intervention Logistics

Our technical interview exercises were designed after taking input from the students in Week 2 of the Fall 2020 intervention semester. In the second week of our course, we added a few optional ungraded questions to the first quiz which asked students about their familiarity with technical interviews. Most students (58% or 143 of the 248 students who answered this question) were not familiar with the technical interviews. Quite a few students (30% of 248, n=75) were familiar with technical interviews but had not participated in them. The remaining students had participated in a technical interview but failed to secure an internship (6%, n=14), cleared a technical interview and had interned (6%, n=14), or were not interested in computing careers (2%, n=5). Three students selected more than one statement and hence the numbers don't add to 100%. Since the awareness of the technical interview process was quite low, we decided to incorporate two activities: a panel and a role-play exercise conducted by the peer mentors and TAs before asking students to participate in mock interviews (see Figure 5).

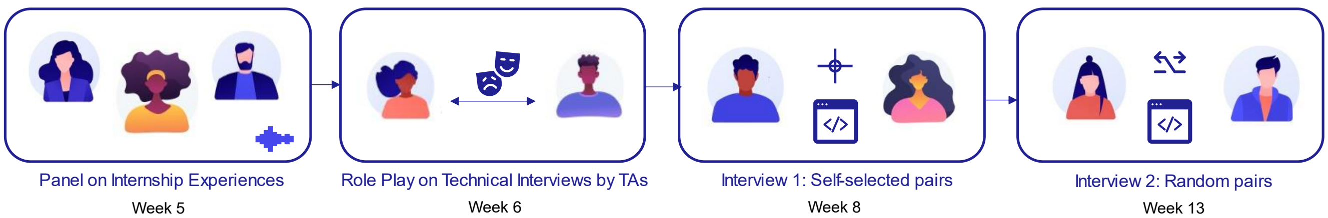

Figure 5. Logistics of Embedding Hire Thy Gator Technical Interview Exercises as reported in Kapoor et al. (SIGCSE 2023)

5.4.1 Panel

The first activity was a panel hosted in Week 5 of our course. The goal of the panel was to make students aware of the importance of internships and introduce them to the recruitment process. The panel consisted of four undergraduate peer mentors (TAs) and was moderated by the instructor. All four TAs had worked as interns in top tech companies in the US such as Alphabet and Microsoft. The panel revolved around the technical interview process, former participation experiences, and the strategies TAs used for successfully securing an internship. This panel was conducted outside of course hours and lasted 45 minutes.

5.4.2 Role play demonstration

The second activity consisted of a role-play demonstration which was organized in Week 6 of our course. During this exercise, the TAs role-play acted as an interviewer and an interviewee in a weekly discussion session to show students what they could expect in a technical interview. We emphasized an iterative approach to solving a problem and underscored the importance of asking follow-up questions as well as writing pseudocode or explaining the solution in words before writing actual code. We also highlighted that interviewers can provide hints if the interviewee is stuck for too long. The role play exercise ended with a conversation between the interviewer and interviewee reflecting on the strengths and weaknesses of the interviewee and how an interviewee can improve. Although the latter conversation is not a part of an actual technical interview, we wanted student interviewers to understand how to conduct a discussion after the mock interview for providing constructive feedback to the interviewee. The reflection and feedback components were added as our activities are formative and the feedback can better prepare students for subsequent interviews. The peer mentors spent three hours preparing for this exercise and the actual class discussion session lasted another 50 minutes.

5.4.3 Mock interviews

After the role-play demonstration, students were asked to work in pairs for two mock interviews in the middle of the semester (Week 8) and the second-last week of the course (Week 14). In the first mock interview, students were allowed to self-select peers with whom they wanted to work. If they could not find a partner, the matching was facilitated by the instructor. In the second mock interview (Week 14), we randomly paired them with another student. This allowed us to scaffold the social interaction of the students and reduce the interview anxiety which is common in technical interviews [11, 46]. In each activity, the students were asked to interview each other with every student acting as an interviewer and an interviewee. We wanted students to act as an interviewer so that they can gain exposure to the recruitment side. In addition, we wanted to make the activity scalable for large classes where the course staff does not have enough resources to interview each student individually. This setup allowed minimal resources with the necessary benefits of exposure to a technical interview.

The activity descriptions were created on our learning management system (LMS), Canvas. Each student was asked to fill out two graded survey assignments for each round of interviewing: one as an interviewee, and another as an interviewer [83]. To help students prepare as an interviewee or an interviewer, we also provided optional resources in survey descriptions such as YouTube videos from Google on what interviewers seek out from candidates in a technical interview or from Gayle McDowell, the author of Cracking the Coding Interview [98] on how to approach technical interviews. The descriptions also consisted of links to two sample interview questions.

The assignment descriptions also had instructions for the interviewer and interviewee. Interviewers were asked to (1) research the question they were going to ask the interviewee, (2) coordinate the time, (3) record the interview and keep track of the solution document, (4) give the interviewee hints if they are stuck for too long, and (5) provide actionable feedback to the interviewee reflecting what were the strengths of the interviewee and what can the interviewee improve on. We asked interviewers to record the interview using Zoom and provide the candidate with a Google document link to write the solution. We also suggested to the interviewer a 40-45 minute window for the technical interview and a 15-20 minute post-interview session on giving actionable feedback to the interviewee. If students spent less than 20 minutes on the activity, we required them to ask an additional technical question or conduct the activity again. For the first set of interviews, interviewers were supposed to pick a question on Trees or Heaps, and for the second one on Graphs or Sets and Maps which are common topics that are covered in technical interviews [98]. This alignment was based on the topics covered in our course during respective times. After the interview, the interviewer was supposed to fill out a survey where they entered a link to the recorded interview, the solution document, and a few reflection questions on their as well as the interviewee's performance. They were also asked for feedback on our activity.

The interviewee's assignment had a description of their responsibilities. They did not know the question beforehand, but they knew that the interviewer would ask questions about the covered topics. The interviewees were told to walk through their approach to solving a problem before coding the solution, ask questions to clarify constraints, improve their solution iteratively, and walk through their solution with a test case to identify any possible bugs. After the activity, the interviewees reflected in the survey their strengths and weaknesses and their experience in the activity. Instructors can find all relevant materials to incorporate our exercises here [83].

The mock interviews were graded based on participation and carried 8% of the points of the final grade (2% for acting as an interviewee and 2% for being an interviewer for each activity). Students (N=257) self-reported average time for preparation and participation in the interview was 2 hours for acting as an interviewer and 1 hour 52 minutes as an interviewee per activity.

5.4.4 Time requirements

To sum up, practitioners replicating the technical interview preparation activities can expect to utilize 6 hours of fixed time to introduce these activities. This time includes 1 to 2 hours of course instruction time for conducting the panel and role-play demonstration and 1 to 4 hours of preparatory time for setting up and organizing the activities. Additionally, variable time spent would cost another 1 to 2 minutes for grading each student submission per activity. The latter time would be more if an instructor wants to provide personable feedback to each student.

5.5 Lessons Learned for Logistics of Subsequent Activity Offerings

5.5.1 Pairing facilitation

A problem that quite a few students (approximately 15-20%) faced was a lack of communication and scheduling issues with their assigned partner. We received several messages on our discussion tool regarding these issues which are an overhead, especially in large classes. We mitigated these problems by assigning a new partner who had a similar issue. In hindsight, we should have provided two deadlines for each interview activity: (1) communicate with the partner and set up the time for the interviews, and (2) the deadline for the actual interview and deliverables.

5.5.2 Alternate assignment for students interested in careers other than computing

4% of students did not participate in the interview activities. The instructor reached out to these students asking if they wished to justify why they didn’t participate and offered them an alternate assignment as it had a non-trivial impact on student grades. Five students responded that they did not participate because of social anxiety, lack of interest in CS jobs, or lack of time. For instance, a student stated, “*There were a few reasons I didn't complete the assignment, the main ones being my social anxiety/difficulty interacting with people I don't know [...] and that I am not expecting to look for/apply for a job in this field*”. The students who did not participate were given alternate coding problems. We recommend other instructors offer alternate activities for such students.

5.5.3 Reduction in grading weights to account for time

Our assumption was students would spend 7 to 8 hours preparing and participating in each round of an interview for both roles. However, the self-reported time spent was less than we anticipated, and students spent on average 4 hours per interview. Hence, in subsequent iterations of the course, the grading structure was reevaluated to account for the time spent and the grading percentage was reduced from 8% to 5% for participating in the two activities.

5.6 Evaluation Methodology

5.6.1 Study design

Our study uses a survey based retrospective post then predesign [125]. In this design, a survey is disseminated at the end of an educational activity or program, to gauge a participant’s change in attitudes, knowledge, or confidence. Data is collected only once, and participants state their confidence level at the end of an activity (post) and retrospectively gauge their confidence level at the beginning of the activity (pre). This type of study avoids pretest sensitivity and response shift bias that result from pretest misestimation. Response shift bias occurs when participants use different frames of understanding about a question between pre and post intervals [67]. Prior studies have shown higher validity of this design than a traditional pre and post design when comparing results with interview data and hence this design was chosen [174] To evaluate our intervention, we use data from a research survey disseminated at the end of control and intervention semesters and interview reflection surveys which were completed by the students after each of the mock interviews. Through our evaluation, we seek to answer the following research questions:

RQ1a. What do undergraduate computing students gain from participating in mock interview exercises?
RQ1b. How does participation as an interviewer differ from participating as an interviewee?
RQ2. How does participation in technical interview preparation activities influence students' perceived confidence levels for programming in a technical interview?

5.6.2 Study participants

Our study was approved by the Institutional Review Board at the University of Florida. 345 students were enrolled in our course in Fall 2020 and 279 students consented to the study (Response rate: 80.9%). Of the 279 students, 22 students' data were discarded due to missing data. Thus, our intervention corpus consists of 257 students. In addition, 143 students enrolled in our course in Summer 2020. The data from this cohort was used as a control group as our activities were introduced after this semester. For Summer 2020, 115 students consented to research (Response rate: 80.4%). Our control group corpus consists of data from 106 students after deleting missing values. Participant demographics are shown in Table 17 and gender proportions in our sample are representative of the student population enrolled in the CS/CE degree program at our institution.

Table 17. Demographics of students who participated in our study as reported in Kapoor et al. (SIGCSE 2023)

Term	Academic Standing (By Year)					Gender			Major			
	1	2	3	4	5-6	Male	Female	DWTS*	CS	CE	CS Minor	Others
Control, N = 106	8%	37%	41%	10%	4%	76%	24%	-	67%	15%	7%	11%
Intervention, N = 257	0.4%	62%	26%	10%	1.6%	71%	28%	1%	66%	18%	10%	6%

*DWTS: *Did not wish to specify*

5.6.3 Data collection

In this study, we use data collected from a post research survey during the control and intervention semester (for answering RQ1a and RQ2) as well as student reflections which were a part of the technical interview deliverables collected during the intervention semester (for answering RQ1b). On average, students spent 22 minutes filling out the research survey which asked them questions on demographics, professional identity, the efficacy of professional development intervention, and how they prepare for technical interviews outside of coursework. The questions we use from these instruments in this section and how they map to our research questions are described in Table 18.

5.6.4 Data analysis

To answer RQ1a (*What do undergraduate computing students gain from participating in mock interview exercises?),* we coded open-ended responses using inductive content analysis [19] to identify the affordances for our activities using student perspectives. We supplement our exhaustive codes with representative quotes to demonstrate what students gained from our activities.

Table 18: Mapping of collected data and research questions as reported in Kapoor et al. (SIGCSE 2023)

Research question	Survey question	Question Type/Scale
RQ1a. What do undergraduate computing students gain from participating in mock interview exercises?	1. How was your experience in Hire Thy Gator Interview Exercises? Should they be a part of future course offerings?	Open ended
RQ1b. How does participation as an interviewer differ from participating as an interviewee?	1. Acting as an interviewer increased my *self-confidence* to succeed in a technical interview in the future[#]. 2. Acting as an interviewer increased my *familiarity* with the technical interview process[#]. 3. Acting as an interviewer is a *useful activity* that is beneficial for me to succeed in a technical interview[#]. 4. Acting as an interviewer allowed me to *understand my weaknesses and strengths* to succeed in a future technical interview[#].	5-point Likert scale: Strongly disagree (0), Disagree (1), Neither disagree nor agree (2), Agree (3), Strongly agree (4)
RQ2. How does participation in technical interview preparation activities influence students' perceived confidence levels for programming in a technical interview?	1. How confident were you with your ability to program in programming interviews before the starting of this course?* 2. How confident are you with your ability to program in programming interviews at the end of this course?*	5-point Likert scale: Not confident (0), Slightly confident (1), Moderately confident (2), Confident (3), Extremely confident (4)

The above questions were repeated to gauge students' perspective on participation as an interviewee (e.g. Acting as an interviewee, increased my *familiarity* with the technical interview process)
* These questions were included in the survey presented to the Intervention and Control groups. All other questions were asked to participants of the intervention cohort.

For answering RQ1b and RQ2, we took a quantitative approach. For RQ1b (*How does participation as an interviewer differ from participating as an interviewee?*), we coded five-point Likert scale statements for four metrics (self-confidence, familiarity, self-evaluation, and usefulness) to 0-4 and then applied nonparametric statistical tests to determine significance of our results across the population of undergraduate students. A two tailed Wilcoxon Signed-Rank Test for paired samples was used as our data did not follow a normal distribution (as identified through a Shapiro Wilk test). Alpha was set to 0.05. The null hypothesis for these tests asserts that the medians of the two samples are identical. For example, one of our null hypotheses was: *There is no difference between the median students' reported confidence gain when participating as an interviewer and an interviewee in the technical interview preparation activities.* Similar hypotheses were used for gauging if participating in our activity increased students' familiarity with the technical interview process, supported self-evaluation, and were overall useful for future success for each role.

For RQ2 (*How does participation in technical interview preparation activities influence students' perceived confidence levels for programming in a technical interview?*), a two-tailed Mann-Whitney U Test was conducted to evaluate differences in pre- and post-data from independent samples as our data did not follow a normal distribution. The null hypothesis for these tests asserts that *the median pre or post students' confidence levels of the two samples (control and intervention) are identical* and a p-value < 0.05 was used to reject the null.

Additionally, we used a confidence gain metric similar to Hake's learning gain metric [36, 57, 58] as there was a significant difference between the pre-confidence levels of our control and intervention cohorts. The confidence gain metric would account for cohorts that may have higher confidence than others when they begin the semester, and it was computed as:

$$\text{Average normalized confidence gain, } \langle g \rangle = \frac{\langle \%\ \text{Post} \rangle - \langle \%\ \text{Pre} \rangle}{100\% - \langle \%\ \text{Pre} \rangle}$$

where, <% Post> and <% Pre> measures are the final and initial course averages of self-reported confidence computed as a percentage. Our confidence gains are computed at a classroom level (gain of averages method, [57, 102]).

5.7 Results and Findings

5.7.1 Affordances of our activities (RQ1a)

To answer RQ.1a. (*What do undergraduate computing students gain from participating in mock interview exercises?*), we asked students in a survey at the end of the course, "*How was your experience in Hire Thy Gator Interview Exercises? Should they be a part of future course offerings?*". 257 students answered this open-ended question, and we categorized their responses using inductive content analysis [19] to identify affordances and benefits of our activities as well as explore students' preferences for continuation of our activities.

Students who participated in our Hire Thy Interview technical activities described that mock interviews impacted them in different ways. The affordances of the activities from students' viewpoint were categorized into nine exhaustive codes. These codes were: (1) awareness of the technical interview process, (2) preparation for future technical interviews, (3) motivation to apply for internships/jobs, (4) opportunity for applying the coursework more practically, (5) building students' confidence, (6) reducing anxiety/fear, (7) providing a low stakes environment, (8) scaffolded interview practice and (9) self-evaluation of one's strengths and weaknesses. Representative quotes on each of these affordances are shown in Table 19.

Regarding continuation of our activities in future semesters, 91.8% of the 257 students (n=236) described our exercises positively stating that they should be continued in the future offering of our course as-is or with minor modifications. For instance, S11 described the intervention as "*a great experience because it gave [her their] first glimpse of an actual industry interview setting"*. She added that "*they should be a part of future course offerings*". 6.2% of the 257 students (n=16) had a negative experience with our exercises and stated that the interviews should be discontinued in the future, or students should have an alternate activity to participate in. One such student was S11 who stated that the interview exercises "*are a good idea in concept, but perhaps don't have a great place in the course. It is overly awkward and not overly helpful in making students better at technical interviews".* 2% of the 257 students (n=5) were neutral about their inclusion and reported that it did not impact them. For example, S56 reported, "*They really have no impact on me as a CS minor. I feel that for the majority of the class (CS(E) majors) they are helpful. I am not sure on how that could be dealt with in future courses".*

Table 19. Affordances of mock interviews

Affordance (Codes)	Representative Quote
awareness of the technical interview process	*"I believe that the [interview] exercises were important in getting familiarised with the programming interview process. This is especially true for people like me who had never done a live programming interview before".*
preparation for future technical interviews	"*I think it was really useful and prepared me well for interviews in the future*".
motivation to apply for internships/jobs	*"The [interview] exercises taught me alot about what to expect in a technical interview. Usually I use my portfolio to get [me] small jobs freelance, but a full scale interview got me very excited to someday do an internship."*
applying the coursework more practically	"*These were really good for contextualising our course content with something that is very relevant to all of us looking for jobs and internships".*
building students' confidence	"*The [interviews] massively improved my confidence for interviews."*
reducing anxiety/fear	*"I think these should be continued as they are great for people like me who have never touched anything remotely close to a technical interview. I think it takes away the uncertainty and fear of these interviews to an extent as it also lets you collaborate with classmates and see their point of views as well."*
providing a low stakes environment	*"[Interview] activities helped me feel more prepared for job interviews and were a relatively low stress manner to practice without too much time commitment. For that I appreciated them."*
scaffolded interview practice	*"The way it's laid out with you being able to do it with a friend for the first time and then with a stranger is also useful. It's really made me a lot more comfortable with coding in front of others. It should definitely be kept."*
self-evaluation of one's strengths and weaknesses	*"I liked them and they revealed things I need to work on before I do another technical interview."*

5.7.2 Efficacy of Role in an Interview (Acting as an interviewer vs interviewee RQ1b)

We were also interested in understanding the impact of interview roles on students' perception of the efficacy of our activities. To compare the impact of these roles (interviewer and interviewee) and answer RQ1b (*How does participation as an interviewer differ from participating as an interviewee?*), we quantitatively determined student responses to four Likert scale measures which were collected in graded surveys for each mock interview and each role. These statements (see Table 18) asked students to rate the contribution of a role (interviewee or interviewer) on (1) increasing self-confidence, (2) improving familiarity, (3) affording self-evaluation, and (4) deeming usefulness of the activity for future success in technical interviews. Students agreed or disagreed to the statements using a 5-point Likert scale (recoded 4 - Strongly agree, 0 - Strongly disagree).

In general, students' average ratings on the contributions ranged from 3.06 to 3.54 out of 4.00 indicating agreement or a strong agreement for each of the roles and for each activity (see Table 20). We also observed that **students perceived participating as an *interviewee* had higher value than participating as an *interviewer* for** each of the measures for both activities. For **two metrics, self-evaluation and usefulness**, the results were statistically significant ($p < 0.05$) for both rounds of interviewees and we rejected our respective null hypothesis. This indicates that students' perceived participation as an interviewee yielded a better mechanism to self-evaluate one's strengths and weaknesses and is considered more useful for future success in technical interviews than acting as an interviewer. For one metric, increasing familiarity, we failed to reject the null hypothesis for both activities indicating that students' perceived participation as an interviewer or an interviewee offered comparable familiarity with the technical interview process. For the last metric, increase in self-confidence, results were significant for round 2 of interviews while not significant for round 1. This means that participating as an interviewee or an interviewer may or may not have equal benefits of increasing confidence and further evidence is required to make a stronger claim. Qualitatively, students mentioned in their responses that participation as an interviewer also has value as they gained insight into tips and expectations for subsequent interviews and alternate ways to solving a problem which they did not gain from participation as an interviewee.

Table 20. Impact from acting as an interviewer vs participating as an interviewee (N = 257)

Activity	Metric	Mean Likert Scale Rating (0-4)~ **Interviewer** (a)	Mean Likert Scale Rating (0-4) **Interviewee** (b)	**δ**(b-a)	Wilcoxon Signed-Rank Test	
					Z	p-value, (**α** = 0.05)
Interview Round 1	↑ familiarity	3.44	3.49	0.05	1.2	0.23
	↑ self-evaluation	3.23	3.46	0.23	5.1	**< 0.001***
	↑ usefulness	3.32	3.52	0.20	4.9	**< 0.001***
	↑ self-confidence#	3.06	3.11	0.05	1.4	0.15
Interview Round 2	↑ familiarity	3.46	3.48	0.02	0.6	0.53
	↑ self-evaluation	3.23	3.52	0.29	6.1	**< 0.001***
	↑ usefulness	3.37	3.54	0.17	4.4	**< 0.001***
	↑ self-confidence#	3.15	3.27	0.12	2.9	**0.004***

N = 256 as one paired data point was missing and ignored
* Statistically significant, p < 0.05
~ 0: Strongly disagree and 1: Strongly agree

5.7.3 Efficacy in building confidence

To evaluate the efficacy of our interview preparation activities on building students' confidence and answer RQ2 (*How does participation in technical interview preparation activities influence students' perceived confidence levels for programming in a technical interview?*), we asked students to gauge their confidence in their ability to program in technical interviews before and after the course in both cohorts. We hypothesized that participation in our activities would improve students' confidence. However, there was a difference in the pre-confidence levels of our control and intervention cohorts. The mean confidence reported at the start of the semester (pre) by the students in the control group was 1.2 (on a scale of 0-4) while that of the intervention cohort was 0.7 (see Figure 6a). This difference was significant ($Z = 4.9$, $p < 0.001$). The students in the control group were enrolled in the first semester post the onset of Covid-19 and most students were not participating in internships because of the pandemic. The higher confidence scores could be because of the fact that students had less fatigue, and these levels were an anomaly compared to subsequent semesters. However, since we introduced the intervention and students reported significant benefits of the activities, we would prohibit students from the benefits of these activities if we were to reevaluate the efficacy using a new control group. This may violate the educational equipoise principles [61] and hence we recommend researchers who have not offered these activities to verify the efficacy of our activities. There was no significant difference in post confidence levels between the control ($PostSummer_{2020}$ = 2.2) and intervention ($PostFall_{2020}$ = 2.1) group, Z = 1.47, p = 0.14 suggesting that the post confidence levels were almost similar for both cohorts.

Since there was a difference between the two cohorts' pre-measures, we computed the average confidence gain of the intervention and control cohorts. The overall average confidence gain of the control semester cohort was 0.36 while that of the intervention semester was 0.42. The change in confidence levels is shown in Figure 6b. It is evident from this figure that during the intervention semester, a higher percentage of students had a greater boost in confidence levels (40% of students had a 2-point jump in the intervention cohort compared to 22% of students in the control cohort and 7% of students had a 3-point jump in intervention cohort compared to 1% students in control cohort). This difference in confidence gains could either be attributed to our interview activities or graded programming problems. Nevertheless, the increase in confidence gains and student recommendation on the usefulness of our activities is promising.

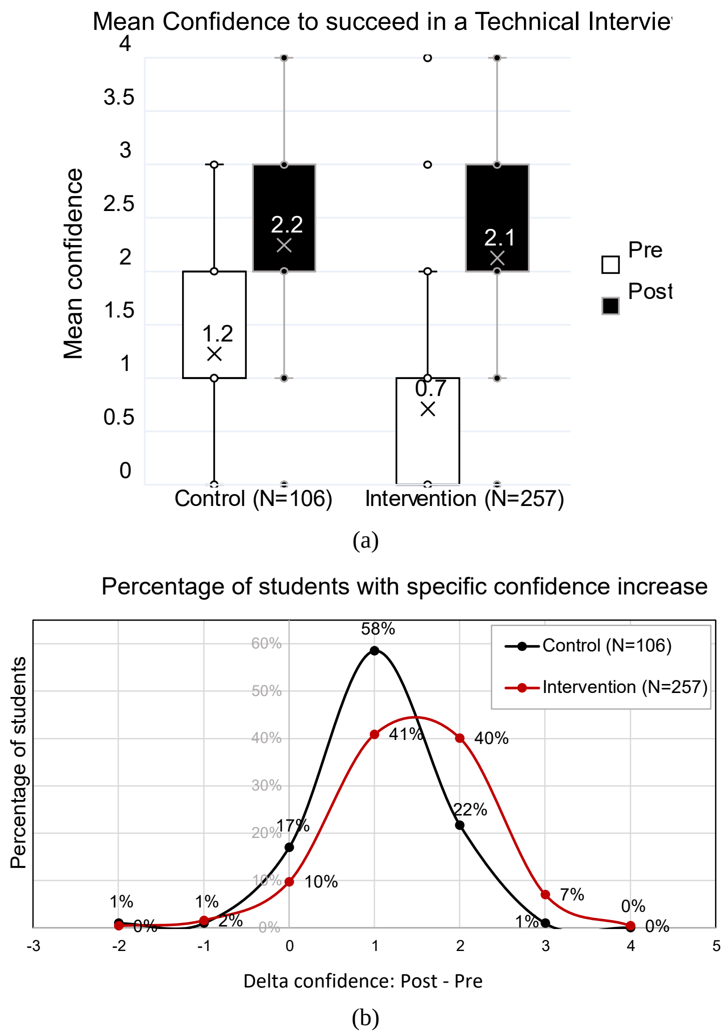

Figure 6. (a) Box plots of Students' aggregate confidence across cohorts; (b) Change in confidence levels between pre and post for the two cohorts

5.7.4 Rooms for improvements in our activities

The 8.2% of 257 students (n=21) who stated that these activities should be discontinued or those who mentioned improvements in future offerings of the mock interview exercises highlighted the challenges associated with our activities. 76% of these 21 students (n=16) who didn't like the exercises mentioned that they were not CS majors and were not interested in computing jobs. For instance, S318, stated "*I didn't prepare for them seriously because as an accounting major, I will not undergo technical interviews to get a job. I think they are very valuable for computer science majors".* Some students also mentioned that the exercises were stressful for them and demanded too much time. Other rooms for improvement were primarily logistical. Students recommended to give them an interview question list from which they can pick a question, allow using text editors instead of a Google doc, make them do exercises as a part of extra credit and not a part of their course grade, reduce the interview time length requirement, add a segment on behavioral questions apart from the technical ones, and match the partners based on skill levels. We recommend Instructors provide alternative exercises for students who may not be interested in technical careers. Further, we invite researchers as well as system designers to build systems or processes for better pairing students for mock technical interviews based on their competencies.

5.8 Discussion and Conclusion

In conclusion, we presented the implementation and evaluation of our technical interview activities, adding to the computing education research literature rich descriptions of our pedagogical activities and empirical results regarding its' efficacy. While prior work has focused on incorporating coding exercises in the curriculum to prepare students for technical interviews [151], our work provides an intervention that is closer to an actual technical interview. Moreover, our formative activities can be used as scalable collaborative assessments in large classrooms with minimal time overheads. Similar to prior work which reported that students find interviews stressful and anxiety-inducing [11, 46], we also observed a few students describing that the interviews were stressful. However, our activities were graded based on participation and not correctness and we introduced measures to scaffold the social anxiety such as allowing them to self-select partners in the first round of interviews. Regarding evaluation, the activities were well received, made students aware of the recruitment process, and suggested agentic development in students' offering them an avenue to self-evaluate and develop confidence to secure a future internship. Therefore, we recommend other instructors introduce these exercises, especially in DSA courses given the overlap with course content. Also, we recommend the instructors to give students alternate exercises who are not interested in pursuing a computing career. In the future, we will determine the efficacy of our exercises for securing actual internships by retrospectively gauging student opinion regarding the value of our activities beyond the course.

5.9 Limitations

To evaluate our activities for confidence building, we compare data from the intervention semester with a previous semester's data. Both cohorts were taught by the same instructor. There were however two differences between the offerings. Both changes pertained to the grading structure, but the course content was the same. First, we introduced graded participatory coding exercises. The problems were available to the students in the control group, but they were optional. However, in the intervention term, students could receive 5% points if they attempted 21 or more of the 55 problems. This change in the grading rubric was based on the control cohort's feedback which mentioned that students were spending significant time on these problems and found them useful for interview preparation. Second, we introduced the mock interview exercises which carried 8% points of final grades. Hence, to account for students' time on our formative activities, we made room in the grading rubric for the intervention cohort. 2-3% points were reduced from other assessment grade weights. The scope of these assessments was adjusted to make up for the increased workload. Our assessment of the intervention for building confidence could be attributed to a combination of the two activities (graded short programming problems or mock interview exercises) which pertained to technical interview preparations. In the future, the efficacy of the activities can be assessed in isolation through more structured quasi-experiments.

5.10 Lessons Learned for Subsequent Studies

Our activities exposed students to technical interviews and developed confidence in them for succeeding in future technical interviews. However, we have not analyzed empirically the efficacy of our activities in aiding students to secure actual internships after our intervention. I did receive several unsolicited emails from students in subsequent semesters that our activities and course helped them in securing internships. For instance, a student stated that she "*found the Hire Thy Gator exercises to be incredibly helpful and that [me] and the TA's went above and beyond to prepare students for interviews and industry. Particularly, [TA-anon1] and [TA-anon2] gave me incredible advice and I just accepted a great software engineering internship for this summer!*". Other students stated that, "*thanks to [our] teaching, [he] was able to successfully answer a technical question at career showcase. [This] resulted in an offer for an interview from the company!*" and "*I took your class, Data Structures & Algorithms Fall 2020 which I thoroughly enjoyed! [...] Your encouragement and preparation for technical interviews for our careers was one of the best outcomes I've ever had from a course!".* To systematically understand the efficacy of our activities in helping students secure internships in our population, we propose a retrospective survey based empirical study which will be described in Chapter 7. The results from this proposed study can corroborate or refute our anecdotal evidence.

Part III: Proposed Work

6. Developing Personas: Fitting in altogether

6.1 Introduction

The central research questions my dissertation will answer is *How do computing undergraduate students* ***secure*** *and* ***participate in*** *internships? What barriers prohibit them from participating in internships?* As a part of this research, I want to identify the attributes and behaviors that distinguish students who successfully secure and participate in one or more internships before graduation from those who do not. Therefore, in this proposal, I seek to answer another sub-research question (PRQ.1): ***How are computing undergraduate students who successfully secure internships different from those who have not interned?***

To answer this research question (PRQ.1), I propose to develop data-backed descriptive personas highlighting characteristics of students who successfully participate in internships and those who do not. Personas in user centered design are personalized fictional characters that embody characteristics of a user type [92, 129]. Personas are developed based on demographic and behavioral user information collected via qualitative research methods such as surveys and interviews or ethnographic inquiries observing users. They provide descriptive models that give insights into users' common goals, motivations, attitudes, and behaviors [38]. In my case, the user type is a *computing undergraduate student,* and the outcome of interest is *participation in an internship (successful or unsuccessful).* We collected data using a survey, semi-structured interviews, and a resume document which is further explained in Section 6.3 and 6.5.

Given the value students receive from participating in internships [77] and our observation that a minority of students pursue internships [80], **our goal is to identify and disseminate how students can secure internships to stakeholders involved in the career development process and strengthen our curriculum for supporting students to secure employment**. Personas were selected as a design tool as they have the ability to communicate compelling stories over abstract data [127] to a variety of stakeholders involved in the students' professional development process such as instructors, students, parents, higher education administrators, career development and industry professionals, etc. empathetically. The personas I will develop will be contextualized in student goals and learning trajectories and use authentic quotes to back findings. In addition, the personas will emphasize students':

1. participation in the formal academic program,
2. involvement in informal and non-formal learning activities,
3. preparation process and strategies for securing internships,
4. barriers encountered when securing internships,
5. interaction with stakeholders that support career development.

We will further elaborate on the methodology for the development of our personas in Section 6.6. These personas can inform the community on student recommended resources for excelling professionally and provide insights on how higher education stakeholders can strengthen their degree program to improve employability of their students.

6.2 Prior Work

User personas were first introduced by Alan Cooper as a practical interaction design tool in his book, "*The Inmates are Running the Asylum"* [37] and they gained rapid popularity in the software industry for their power and effectiveness [128, 175]. Personas are archetypes of users based on actual data that narrate realistic types of users based on clusters of goals, attitudes, and behaviors [16, 17, 176]. Within Computing Education Research literature, personas have been used as (1) a pedagogical tool in classroom practice to describe or identify design requirements [9, 21, 22, 27, 107, 120, 141, 148, 158] or for generating awareness on social topics such as diversity [134], (2) a conceptual tool to guide research design and inform research study interventions [29, 90, 114, 119], (3) a design tool to collect data regarding a subject's decision-making process [30, 31], and as (4) an analytical tool to categorize or visualize empirical research data [52, 85, 105, 111, 112, 146, 161].

Research that has used personas as a *pedagogical tool* to describe or identify design requirements include Mohan and Chenoweth's work [107] which described an innovative curriculum for software engineering or senior design courses which allows learners to gain hands-on experience on requirements elicitation and management techniques. They proposed that students should use personas for problem analysis and interact with faculty who role played as personas to elicit requirements. Letaw et al. [90] used GenderMag's personas as a *conceptual tool* to inform the design of their curricular intervention promoting inclusive design and Chinn and VanDeGrift [30, 31] used personas as a *design tool* to collect data regarding a students' decision-making process. In the latter study, they gained insights into students' decision-making process related to hiring in the software industry by providing students four personas of potential hiring candidates and asking them to list their criteria for evaluating the candidates.

Work that has used personas as an *analytical tool* to categorize or visualize empirical research data include Nelimarkka and Hellas' research [111] who used personas to present a typology of social learning strategies used by five types of Massive Open Online Course (MOOC) learners. These personas described learners that had the following help seeking strategies: computer-mediated friend-based interaction, non-helpseekers, friend supported learners, heavy MOOC platform benefiters and MOOC platform benefitters. Their goal was to communicate these personas to course instructors, MOOC system designers, and other stakeholders. Similarly, Newby also categorized online help-seeking behaviors and found two personas: askers and lurkers (those who ask and never ask questions) [112]. They observed that askers performed significantly better on course performance than lurkers. Another work that used personas as an analytical tool is research by Teague [146] who explored why students struggle learning to program using a people-first approach. She described the barriers to programming using rich case studies and student programmer personas which further formed the basis of a design taxonomy categorizing the personas across two dimensions: *confidence* and *determination*.

Our work uses personas as an analytical tool to inductively categorize empirical research data similar to Milliken et al. [105] who described teacher personas using cases in the context of block-based program grading or Teague's work that described student personas who faced barriers to programming [146]. Additionally, we will back our personas with results from our frequency analysis of qualitative codes and use our survey results to triangulate the findings similar to Giannakos et al.'s work [52] which examined the profile of CS teachers and developed personas regarding their knowledge on Technological, Pedagogical, and Content Knowledge.

6.3 Data Corpus

To develop personas of students who successfully participate in internships and those who do not, we primarily use interview data from the data corpus that we collected during Study 2 (Chapter 4). In Study 2, we designed a cross-sectional multi-institutional study to understand how computing undergraduate students participate in internships and other professional development activities. Data was collected through a survey and semi-structured interviews. In Chapter 4, we analyzed survey data, and in this chapter, we propose to analyze semi-structured interview transcripts from our sample of 42 computing undergraduate students. Additionally, we will use students' data from the survey and resumes as needed, to triangulate our findings. These results and findings will inform the development of our personas.

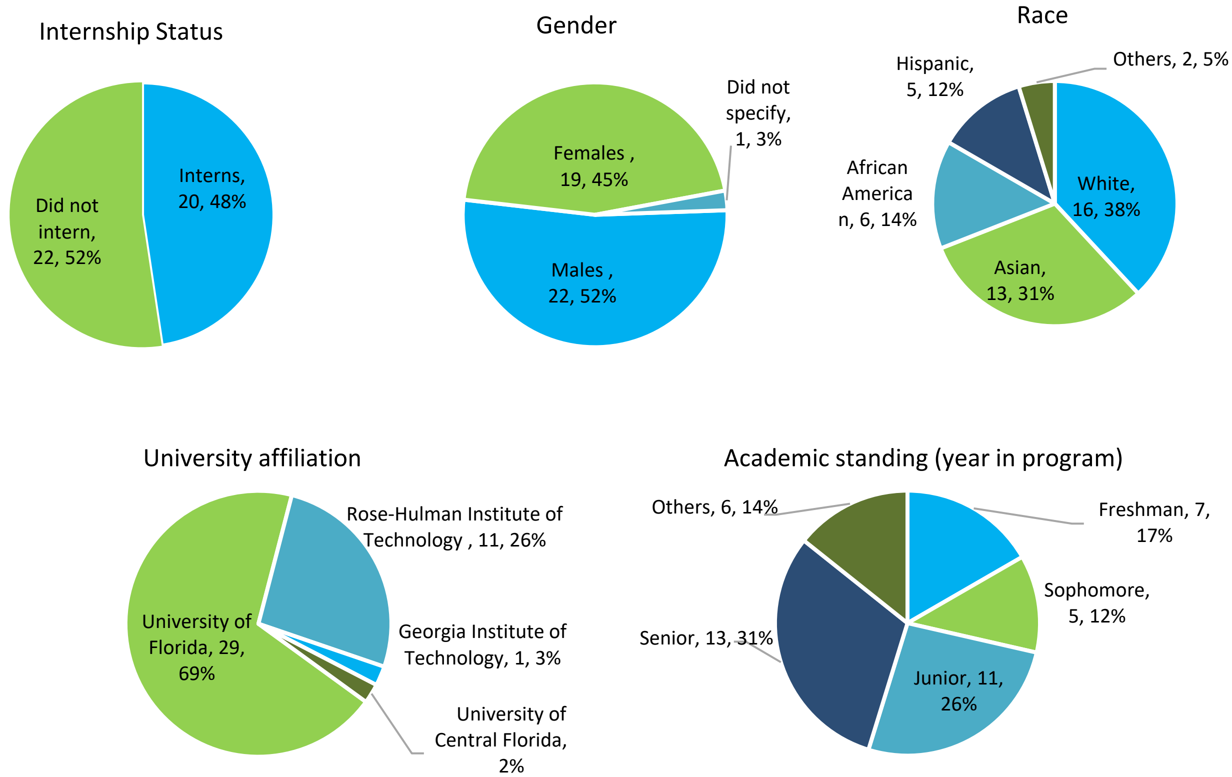

Figure 7. Demographics of Interviewees

6.4 Participants

The computing undergraduate students who were interviewed were purposefully recruited from our survey based on five attributes: (1) Internship status, (2) Gender identity, (3) Racial identity, (4) Year in program, and (5) University affiliation. These attributes were selected to capture representation of student voices regarding internship participation experiences across our study population of computing undergraduate students. Additionally, while we tried to recruit an even number of participants across each demographic, certain recruited demographic distributions were uneven but rather representative of the student population at two institutions: University of Florida (n=29) and Rose-Hulman Institute of Technology (n=11). For instance, instead of an equal number of students from different racial backgrounds, we had twice as many Asian or White students compared to Hispanics or African Americans. We had one interviewee each from the Georgia Institute of Technology and the University of Central Florida (UCF). At the former institution, we failed to recruit interviewees although we proactively reached out to recruit a larger sample using their contact information in the survey. We recruited an interviewee at UCF based on a referral from another student who stated that the candidate had a rich story on how they received an internship and hence we were interested in capturing their experiences. The number of students across each demographic attribute is shown in Figure 7.

6.5 Data Collection

The semi-structured interview questions and script was designed based on our findings from Study 1 (Chapter 3) and our research questions for Study 2 (Chapter 4). My advisor and I co-developed the interview script and resolved any discrepancies or conflicts through conversations until we reached a consensus. Students were selected for the interviews based on their survey responses and resumes. Each interview script was tailored for an interviewee to a limited extent after reviewing their respective response in the survey as well as a comprehensive review of their resume. I interviewed 42 students in 2019 who gave their consent. The students were compensated with a $20 gift card for their time and participation. The average interviewing time was 55 minutes (Range: 21-74 minutes, SD: 10 minutes). The interview script consisted of seven sections with each section consisting of one to seven questions and follow ups which were asked to the interviewee based on their survey, resume, and interview response. These seven sections and sample questions are shown in Table 21. The interview audio was transcribed using a professional service and I reviewed each transcript to ensure they were accurate.

Table 21. Sample interview Questions.

Section	Example Questions
Grand Question	Why did you decide to pursue a Computer Science or Computer Engineering degree?
Career goals and choices	You mentioned you want to become a __________, can you tell me how you got interested in ______?
Preparation for Career	How are you preparing yourself to become a _____ and work in ______?
Professional Experience (e.g. Internships)	**Interned**: You indicated on the survey, you participated in internships in ____ year, tell me the story of how you got your first internship?
	Not an intern (Applied but failed): Through prior research we found that only 40% of juniors/seniors pursue internships, why do you think you haven't *secured* an internship so far?
	Not an intern (Not applied due to lack of confidence, skills, etc.): Through prior research we found that only 40% of juniors/seniors pursue internships, why *haven't you applied* for an internship so far?
Professional Development (e.g. Personal Projects, Clubs, Hackathons, etc.)	You have participated in _____ clubs/hackathons/projects. Out of all these, which was most beneficial for your professional growth as a _______?
Degree Program Experience	How has your CS coursework shaped your professional interest and identity?
Hypothetical	What mistakes did you make during the degree program, which you would advise your junior/brother/sister not to make, if they were to enroll into a similar program in future?

6.6 Data Analysis

To develop the data-backed personas, I will use a collection of qualitative data analysis techniques to understand the characteristics of students that are successful and unsuccessful in internship participation. I will start with individuals as a unit of analysis and then shift to groups as a unit of analysis by creating themes that describe common characteristics of successful and unsuccessful students [40]. Figure 8 visually depicts the steps of the proposed analysis.

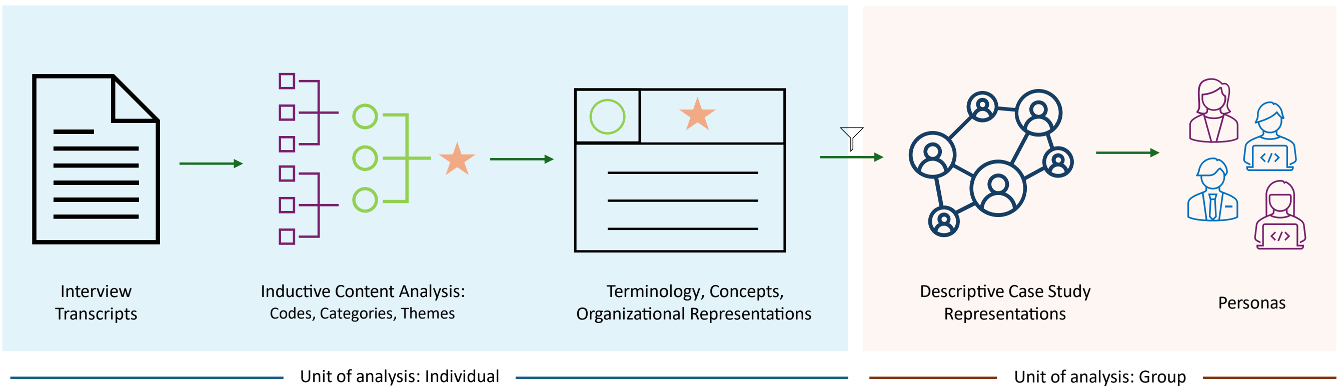

Figure 8. Data Analysis Process of Generating Personas

Unit of Analysis: Individuals. Before analyzing the interview transcript data, I will use an **analytic memo** technique recommended by Miles et al. [104] to capture each interviewee's characteristics and reflect on emergent patterns and concepts I gained from reviewing interviewee's survey response, their resume, and my physical interview notes. Analytic memos involve writing reflective notes and making sketches signifying concepts, patterns, themes, and relationships during or after data analysis. Additionally, they will improve the rigor and trustworthiness of my analysis process by providing a place to document my decision-making process by presenting my personal experiences, biases, and interpretation rationale [104, 135].

After writing a memo for a participant, I will analyze their interview transcript data using **inductive content analysis** [19] in Microsoft Excel. The unit of analysis will be an individual at this point. In this analysis, I will first develop primary codes that capture the semantic and latent essence of the interviewees' responses. The semantic codes will capture interviewees' opinion based on face value or explicit answers while the latent codes focus on underlying meanings in data and look at the reasons for semantic content via interpretation [135]. The codes will be clustered to form categories using the constant comparison technique as suggested by Corbin and Strauss [39], and these will form the basis of my codebook. These categories will be further abstracted into themes which capture tacit attributes and processes regarding students' participation in internships. This analysis technique will be continued until we reach theoretical saturation [39], meaning no new themes emerge from additional transcripts. These categories and themes will provide an organizational structure that identifies the terminologies and concepts such as goals, attributes, behaviors, environments, and processes, etc. associated with students' participation in internships based on our data. Additionally, frequency analysis of the categories and themes will be performed. To validate the themes, an interrater reliability agreement will be performed with two researchers who are not associated with the study and Cohen's Kappa will be computed [101]. I will also release my positionality related to this research and use rich descriptions and quotes from interviewees to back the qualitative analysis.

Unit of Analysis: Groups. In the next step (see Figure 8), the unit of analysis will shift from individual to primarily two groups of students: those who participated in internships and those who did not. I will identify the differences in these two groups and further create sub-groups representing multiple cases which will be presented as rich descriptive case studies [126]. The subgroups will represent cases beyond the dichotomy of successful vs unsuccessful students based on attributes and behaviors and will be drawn from the emerging categories of my previous analysis at an individual level. For instance, if three categories of participation emerge from students who do not participate in internships, then cases will describe each of them as students maybe have distinct trajectories and tailored interventions need to be introduced to solve the problems of practice rather than a one-size fit-all solution. An example of this categorization may be (a) students who are applying for internships and failing to secure them, (b) students who are interested in participating in internships but do not apply due to factors such as low self-efficacy or other socio-economic constraints, and (c) students who are not interested in participating in internships due to other goals. These case studies will further be abstracted into visual persona representations that describe collective student goals, attributes, behaviors, and challenges related to career development for each case. The personas will be used to highlight the problems of research and problems of practice to a variety of stakeholders such as instructors, career development professionals, higher education administrators, etc. so they can use them to design and introduce interventions.

6.7 Limitations

Although personas as a design tool can help communicate the difference between computing students who participate in internships and those who do not to a variety of stakeholders, they do have certain limitations.

First, personas are based on generalized characteristics and behaviors which may not represent diverse students. I aim to resolve the inclusion of voices through (1) purposefully recruited students in our interview sample to understand eclectic viewpoints and (2) by developing multiple personas beyond the dichotomy of successful vs unsuccessful student personas that characterize students based on attributes and behaviors.

Second, there is a risk of creating personas that reinforce stereotypes [124]. I will be transparent about my data analysis process, back the personas using authentic quotes and empirical data from students and declare my positionality with respect to this research to improve reliability and validity of the outcomes.

Third, personas and qualitative research findings can be limited to specific populations and opponents have argued that personas do not “determine how many, if any, users are represented by a persona” [28]. Our goal is to use personas for empathetically communicating the types and challenges of students to the stakeholders in academic programs so they can use these personas to introduce interventions or build inclusive academic programs supporting the needs of eclectic students.

Lastly, since our interview sample consists of students across institutions in the United States (US), the results might not generalize to other geographies where the employment recruitment process or employment opportunities for internships are dissimilar to the US. Nevertheless, our goal was to explore the complex internship participation process in depth. I will provide boundaries, scope, and context on where our findings will generalize to the broader populations and back our findings with a quantitative frequency analysis of our qualitative codes so that the stakeholders can understand the limit and importance of our personas.

7. Study 4: How effective is our pedagogical intervention in preparing students for securing internships?

7.1 Introduction

Our pedagogical intervention, *Hire Thy Gator Technical Interview Exercises,* exposed students to technical interviews and developed confidence in them for succeeding in future technical interviews (Chapter 5). However, we have not studied empirically the role of our activities in supporting students in subsequent interview preparation after our course or for securing actual internships and/or jobs. To understand this efficacy, I propose a final survey-based study where students retrospectively gauge the role of *Hire Thy Gator Technical Interview Exercises,* in supporting them for (a) future technical interview preparation, and (b) subsequently securing an internship or job during their undergraduate program. In this study, we will ask students to describe the efficacy of our intervention, 8-35 months after their participation in our activities. The findings from this proposed study can determine the value of our exercises for aiding students' competitiveness for the job markets.

We aim to answer the following research question through our study (PRQ.2): *How effective are Hire Thy Gator Technical Interview Exercises in preparing computing undergraduate students for securing industry internships?*

7.2 Study Design and Participants

Study design. I plan to run a longitudinal panel survey study [40] in Fall 2024 at the University of Florida. In this design, data is examined from specific cohort(s) over time [40]. This design was selected as I am trying to understand the efficacy of our exercises on the cohort who were exposed to our intervention. I will submit our study proposal to the Institutional Review Board in Summer 2024 and run the survey in September 2024.

Sample. The sample for this survey will be drawn from the population of undergraduate computing students who participated in *Hire Thy Gator Technical Interview Exercises* in my Data Structures and Algorithms (DSA) course that was offered at the University of Florida from Fall 2020 to Spring 2024. These students participated in these activities as a part of the course delivery and assessment (two mock interview quizzes). The cohort of students from Spring 2024 semester will be allowed to participate as they will have an opportunity to apply for internships in the Fall 2024 career fair at the university. Our target population consists of 4340 students who completed my DSA course and submitted course evaluations after the drop/add period. It excludes students who dropped my course (~10%) but may include some duplicates as students who did not earn a passing grade may have retaken the course (~6%). Since Fall 2020 (and excluding Spring 2024), ~215 students did not earn a passing grade for critical tracking (C- or below) and hence our population consists of approximately 4125 students. The students in our sample can inform us of the efficacy of our intervention for subsequent technical interview preparation or for securing internships after they were exposed to our technical interview exercises.

Participant recruitment. Participants will be recruited from courses that students take after my DSA course. Some of these courses include software engineering, programming language concepts, operating systems, human-computer interaction, databases. The students in these courses will be given 1% extra credit towards their final grade for participating, contingent on approval from the respective course Instructor and an alternative assignment requiring equal effort will be provided in case the students do not wish to participate in the study. Additionally, we will also use consented emails of participants from Study 3 for recruitment as these students participated in our activities.

7.3 Data Collection and Analysis

Survey questions and metrics. Our survey will obtain consent from the students and consists of seven sections: survey instructions, demographics, confidence levels, internship participation, preparation practices, intervention evaluation, and subsequent clarification. We have added 42 questions to our survey which excludes questions that will be omitted based on display and skip logic. Selected questions from our survey are shown in Table 22.

Table 22. Survey Questions for Study 4

<table>
<tr><th>Survey Question</th><th>Survey options</th></tr>
<tr><td>Hire Thy Gator (HTG) Technical Interview Exercises consist of an activity where you get paired with another student and participate in mock interviews. Each student in the pair interviews the other student taking turns. Do you remember participating in mock interviews in any course in the UF curriculum?</td><td>▪ Yes, I participated in HTG activities. The course in which I participated in HTG activities was _____
▪ No, I did not participate in HTG activities.
▪ Unsure, I do not remember if I participated in HTG activities.
▪ Others (Please specify)</td></tr>
<tr><td>What role did HTG exercises (mock interviews) play in helping you to secure an internship or a full-time job?</td><td rowspan="2">Open-ended</td></tr>
<tr><td>How did participation in HTG exercises (mock interviews) influence your subsequent preparation practices to secure computing internships and jobs?</td></tr>
<tr><td>HTG exercises (mock interviews) helped me in securing an internship/full-time job.</td><td rowspan="3">Likert Scale - 5 point
Strongly agree - Strongly disagree</td></tr>
<tr><td>HTG exercises (mock interviews) motivated me to
- participate in subsequent mock interviews
- participate in subsequent individual programming practices (e.g., Leetcode style questions)
- apply for actual internships or jobs related to computing</td></tr>
<tr><td>HTG exercises (mock interviews) prepared me to
- participate in subsequent mock interviews
- participate in subsequent individual programming practices (e.g., Leetcode style questions)
- apply for actual internships or jobs related to computing</td></tr>
<tr><td colspan="2">Professional success   Preparation   Motivation</td></tr>
</table>

For my dissertation, I will analyze selected questions from the Fall 2024 survey from the demographics and intervention evaluation sections that answer my proposed RQ2: *How effective are Hire Thy Gator Technical Interview Exercises in preparing computing undergraduate students for securing industry internships?* The survey questions will gauge the efficacy of our exercises on three metrics: *motivation, preparation,* and *professional success* (see Table 22). The **motivation and preparation metrics** will determine the efficacy of our exercises for aiding students to subsequently participate in technical interview preparation (mock interview or individual programming practices, e.g., Leetcode style questions) or apply for actual internships or jobs related to computing.

The **professional success metric** will determine the efficacy of our intervention on securing an actual internship or job. The results from this survey analysis will complement findings from our Study 3 survey (Chapter 5) providing a holistic overview of the efficacy of our activities on students' employment outcomes post their participation in my course.

Additionally, I will compare aggregate data in the two surveys: Study 3, (RQ1a. *What do undergraduate computing students gain from participating in mock interview exercises?*) and this study, regarding what students gain from participating in our activities over a period of time. Similar trends across these two survey results will reinforce the benefits of our activities and provide empirical evidence regarding the effectiveness of our activities that can support other instructors in incorporating them in their courses.

Data analysis. I will use descriptive statistics such as mean, median, and percentages to examine student responses to Likert scale statements for quantitative data. I will analyze qualitative open-ended questions using inductive thematic analysis [19]. We will code the raw data into primary codes, which will be further clustered to form categories, and these categories will be abstracted into themes. To verify the reliability of my coding scheme, my advisor and I will perform inter-rater reliability at the theme level. We will discuss these themes in case of disagreement, clarify the terminology, and recode the definitions in the codebook. This iterative process will be followed until a consensus is reached about the accuracy of the theme descriptions. Then, I will perform a frequency analysis on these codes, categories, and themes. Additionally, I will visualize the descriptive statistics of quantitative data and frequency analysis of qualitative data using common charts such as column charts, stacked bar charts, and pie charts [40, 56].

7.4 Limitations

Locating students who have participated in our technical interviews intervention could be difficult, which is typical of longitudinal panel studies. However, we will purposefully identify the students in upper-level courses offered in the department as well as email students who participated in our previous study (Study 3). Additionally, there might be some students who would have graduated before Fall 2024 when we collect data or students would have dropped out from the program or the computing discipline since our intervention's first offering in Fall 2020. The latter may induce **survivorship bias** in our sample as we do not cover the voices of students who may have dropped out from computing.

Another limitation of our study is the **single group threat** [149] as we do not collect data from a control group of students who did not participate in our activities for this proposed study. Researchers in the future can identify how and when students become aware of the technical interview process and start the preparation process if they did not get a chance to participate in such activities.

Students in our sample are also subject to **maturation effects** as they would have prepared for technical interviews after my course. They may fail to recall our activities and conflate it with mock interviews that they participated in outside of the curriculum or in another course. We have added additional checks to our open-ended questions to ensure that students are answering responses that relate to their participation in our activities. We explicitly ask them to explain the impact of our activities on subsequent interview preparation and for securing a job to better understand the impact of our activities.

Lastly, we will attempt to address the **validity** of our qualitative inquiry through the transparency of our research process, using participants' quotes, as well as revealing the researchers' positionality.

8. Expected Contributions

My dissertation focuses on fundamental research in computing students' participation in internships. My contributions to the Computing Education Research (CER) community and computing practitioners include empirical [72, 73, 77, 80, 156], theoretical, and pedagogical [83, 84] contributions.

8.1 Empirical Contribution

My initial work on identity formation in computing has evaluated how researchers conceptualize and operationalize identity in computing education [82], identified how computing students conceptualize their professional identities [74, 75], the factors and avenues that influence identity formation processes [79], and the chronology of this process [79] in the context of computing undergraduate degree programs. This research provided insight into the crucial role played by informal and non-formal learning environments such as internships, personal projects, student organizations, and hackathons on students' identity formation. Subsequently, I started focusing on the underexplored area of internships in computing while most other research focused on formal education in the context of academic programs [13, 41, 121, 122, 139]. For computing internships, I assessed the impact of internships on undergraduate computing students [77], identified who participates [73, 80, 156] and who does not [72, 73, 156], and explored the preparation processes of students for securing internships [80]. I add to the CER literature the following empirical results:

1. Rich descriptions of
    a. the value computing undergraduate students receive from participating in internships [77].
    b. attributes of avenues where students intern.
    c. students' preparation processes for securing internships [80].
2. Baseline data on
    a. attributes of students' who participate in internships [80, 156].
    b. students' confidence levels to secure internships before and after a course that has an overlap with technical interviews [84].
3. A qualitative categorization model describing students' barriers to participation in internships [72].
4. A statistical model for identifying undergraduate computing students who will likely and not likely participate in internships based on demographics, socio-economic factors, academic factors, external involvement factors, and identity formation [156].

8.2 Theoretical Contribution

My dissertation will also contribute to the CER literature, rich student personas describing their participation in internships. The phenomenon of interest for these personas is to understand the differences between students who successfully participate in internships before graduation and those who are unsuccessful in securing internships. These personas will:

1. describe concepts and relationships related to students' participation and preparation processes for securing internships.
2. highlight salient attributes of students who successfully secure internships and those who are unsuccessful in securing internships.

3. elucidate stakeholders in formal, non-formal, and informal education that are involved in students' participation and preparation process for securing internships.

8.3 Pedagogical Contribution

Since, a substantial number of students fail to participate in internships due to psychosocial and financial constraints [72], I have created and incorporated a pedagogical intervention, *Hire Thy Gator Technical Interview Exercises,* in a large computing core course [81, 84] so that all students can become aware as well as feel prepared for the internship recruitment process. My dissertation also contributes both rich pedagogical descriptions as well as empirical analysis of the efficacy of this intervention. Practitioners and educators can use the open-source resources [83] and learn from the best practices of incorporating our pedagogical activity in instruction. In addition, I have released baseline data on students' awareness and confidence on succeeding in technical interviews before and after the intervention from a sample of undergraduate computing students at a large public university in the USA [84]. This data can be used to tailor the intervention or propose new interventions across other types of institutions depending on student profiles.

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