

How Do Educational Experiences Predict Computing Identity?

STEPHANIE LUNN, MONIQUE ROSS, ZAHRA HAZARI, and MARK ALLEN WEISS,
Florida International University, USA
MICHAEL GEORGIOPOULOS, University of Central Florida, USA
KENNETH CHRISTENSEN, University of South Florida, USA

Despite increasing demands for skilled workers within the technological domain, there is still a deficit in the number of graduates in computing fields (computer science, information technology, and computer engineering). Understanding the factors that contribute to students' motivation and persistence is critical to helping educators, administrators, and industry professionals better focus efforts to improve academic outcomes and job placement. This article examines how experiences contribute to a student's computing identity, which we define by their interest, recognition, sense of belonging, and competence/performance beliefs. In particular, we consider groups underrepresented in these disciplines, women and minoritized racial/ethnic groups (Black/African American and Hispanic/Latinx). To delve into these relationships, a survey of more than 1,600 students in computing fields was conducted at three metropolitan public universities in Florida. Regression was used to elucidate which experiences predict computing identity and how social identification (i.e., as female, Black/African American, and/or Hispanic/Latinx) may interact with these experiences. Our results suggest that several types of experiences positively predict a student's computing identity, such as mentoring others, having a job, or having friends in computing. Moreover, certain experiences have a different effect on computing identity for female and Hispanic/Latinx students. More specifically, receiving academic advice from teaching assistants was more positive for female students, receiving advice from industry professionals was more negative for Hispanic/Latinx students, and receiving help on classwork from students in their class was more positive for Hispanic/Latinx students. Other experiences, while having the same effect on computing identity across students, were experienced at significantly different rates by females, Black/African American students, and Hispanic/Latinx students. The findings highlight experiential ways in which computing programs can foster computing identity development, particularly for underrepresented and marginalized groups in computing.

CCS Concepts: • **Social and professional topics** → **Computing education; Computer science education; Information technology education; Computer engineering education;**

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Authors' addresses: S. Lunn, M. Ross, and M. A. Weiss, Florida International University, School of Computing and Information Sciences, Miami, FL; emails: {slunn002, moross}@fiu.edu, weiss@cs.fiu.edu; Z. Hazari, Florida International University, STEM Transformation Institute, Miami, FL; email: zhazari@fiu.edu; M. Georgiopoulos, University of Central Florida, Department of Electrical Engineering and Computer Science (EECS), Orlando, FL; email: michaelg@ucf.edu; K. Christensen, University of South Florida, Department of Computer Science and Engineering, Tampa, FL; email: christen@cse.usf.edu. Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from [permissions@acm.org](https://permissions.acm.org).

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1 INTRODUCTION

Over the past decade, occupations in **science, technology, engineering, and mathematics (STEM)** disciplines have flourished, with employment rising at 24.4% as compared to only 4% in non-STEM fields [89]. Among the different STEM disciplines, computing and math fields account for almost half (49%) of all STEM employment. As technology continues to expand in capabilities and to proliferate in everyday life, there is a growing imperative to incite interest in computing and to produce more graduates in the field. Between 2019 and 2029, computing fields are projected to experience some of the fastest growth, with rates at 31% for information security analysts and 22% for software developers [90]. Despite the need for expansion, there remains a struggle to engage and retain students in **computer science (CS)**, **computer engineering (CE)**, and **information technology (IT)**. Compared to other STEM majors, undergraduate students in computer/information science have the highest attrition (59%) rates [19]. This divide is particularly concerning in groups already experiencing disparities in STEM fields—women, Black/African-American students, and Hispanic/Latinx students [127].

Since the late 1990s, women account for 57.0% of all bachelor's degrees earned; however, in computer science the number of women receiving bachelor's degrees has dropped from 27.2% in 1997 down to 18.7% in 2016 [88]. For Hispanic/Latinx students, although the percentage of total undergraduate computer science degrees earned has increased (from 5.2% in 1997 to 10.1% in 2016), this value remains low compared to Hispanic representation in the general population (18.3%) [12, 88]. Likewise, Black/African American students are consistently underrepresented among computer science bachelor's degrees (9.6% in 1997 to 8.7% in 2014) relative to their representation in the population (13.4%) [12]. Thus, it is vital that we seek to understand what factors are most important for minoritized students' engagement, retention, and long-term success.

Researchers have begun to explore what may attract or discourage women and racial/ethnic minorities from pursuing degrees and careers in computing [5, 20, 21, 33, 85, 119, 123, 125]. Among these, notions about what or who a computing student is or should look like has been suggested to impact the decision to enroll or persist [14, 20, 33, 85, 125]. Most often, the archetypal computer scientist is described as being intelligent but lacking interpersonal skills, and is perceived to typically be a geeky White and/or Asian male [5, 14, 21, 125]. Such stereotypes are held culpable for discouraging the participation of individuals who do not consider themselves as such and, accordingly, are unable to visualize themselves fitting into that mold. Meanwhile, other publications suggest that a lack of early access or social support is responsible for the dearth of minoritized populations [119, 123]. While indeed many factors may contribute, this unequal representation remains a complex amalgamation of issues that ultimately is impacted by how students view themselves, their experiences, and their long-term goals.

Previously disciplinary identity theory has been applied in STEM fields and has been shown to be a valid and effective way of understanding and predicting persistence and career choice [15, 17, 27, 44, 55, 58]. Although some work has been conducted in computing, overall it remains relatively sparse [80, 92, 97, 112, 113]. Moreover, there remains a gap in understanding with respect to how experiences shape computing identity.

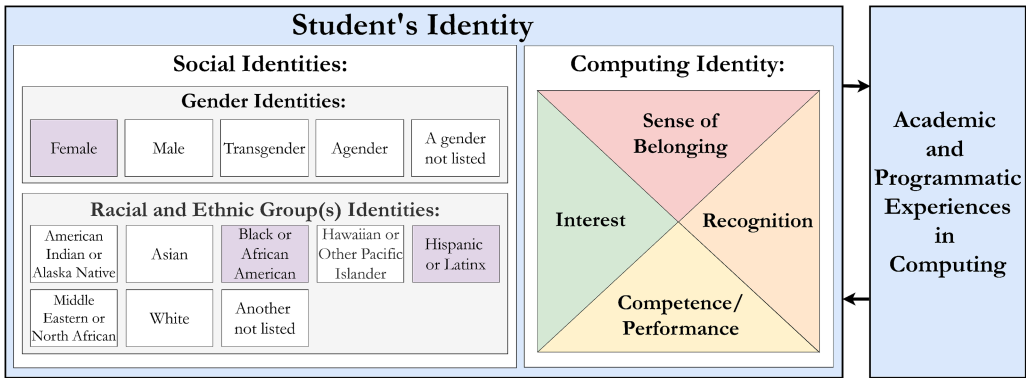


Fig. 1. Computing students' identity as defined by their social identity and computing identity, along with the reciprocal relationship between experiences and computing identity.

Computing identity in this study is defined as the way students see themselves with respect to computing (computer science, computer engineering, and information technology). To reconfirm and expand upon existing work, we conceptualize computing identity for college students using the dimensions of competence/performance, recognition, interest, and sense of belonging, as depicted in Figure 1 [112]. In our context, **interest** is defined by personal engagement with respect to computing, in terms of having an intrinsic desire to study, practice, and contemplate the discipline [80, 113]. **Sense of belonging** is described as a student's feelings of belonging to a community or group related to computing [112]. **Competence/performance** is defined as a student's self-confidence in understanding computing and feeling accomplished in that topic. Finally, **recognition** refers to the internalized perception of recognition a student feels from others such as teachers, family members, and friends [80, 113]. Most frequently, literature and models in computing tend to focus more on encapsulating interest, sense of belonging, performance/competence, and self-efficacy [1, 72, 85]. As such, we want to highlight that recognition is meaningful as well, and that understanding its contribution to computing identity is especially important since this component has been suggested to be critical for engagement of groups underrepresented in computing [62].

As further illustrated in Figure 1, another aspect of a student's identity is their social identity. **Social identities** are defined by the characteristics individuals identify with as a member of a group, and in this work we consider students' gender identities and their racial/ethnic group identities. Boxes in purple denote the underrepresented gender and racial/ethnic identities that we focused on for interactions with experience—females, Black/African American students, and Hispanic/Latinx students. Additionally, in this work, we consider **experience**, which refers to the knowledge, understanding, and skills that result from events, activities, and/or interactions with others [35, 97]. Specifically, our analyses assess academic and programmatic experiences and their interaction with students' identities.

In this study, we surveyed 1,654 students from three metropolitan public universities in the state of Florida, to explore how educational experiences predicted computing identity. Our goals were to (1) reconfirm the sub-constructs of computing identity, (2) examine the relationships between computing identity and experience, and (3) explore the interaction between experiences and the computing identity of groups underrepresented in computing fields (women, Black or African Americans, and Hispanic, Latinx, or Spanish origin students). This research is important to computing fields for the design and planning of curriculum and extracurricular activities and for improving engagement, performance, persistence, and overall academic outcomes.

2 RELATED WORK

Section 2.1 describes how individuals' interactions with the world contribute to their perceptions of themselves and how they act in the world. Although we introduce the broad conceptualization of identity for framing our work, we also focus on a particular type relevant for this inquiry, computing identity. Additionally, since identity can be affected by unique experiences, we present work on academic and programmatic experiences in Section 2.2.

2.1 Computing Identity

Identity is considered a complex, context-dependent, and ever-fluctuating conceptualization that is rooted in a person's position individually and as a member of different groups [42, 78, 111]. Gee defines identity as the "*kind of person*" an individual is and considers educational aspects that contribute to its formation [42]. He highlights the salience of social relationships, discussing how affinity groups (members within a group that share practices or experiences) can be created by others to emphasize distributed knowledge. Schools are an example of this, stressing the importance of learning together in a community. As a result, how students learn and participate shapes their identity.

Meanwhile, the socio-constructivist perspective on identity places further emphasis on interpersonal relationships and social interactions [105]. According to this view, encounters with others are what help to define and reify identity [13]. Lave and Wenger also highlight the importance of a social community and describe how active participation is established and reinforced through an individual's experiences [74, 122]. In computing, this has been shown to be mediated through interactions with others such as friends and family, professors, and mentors [97]. This is particularly relevant to our work, where we explore how different social experiences may contribute to an individual's disciplinary identity.

Disciplinary identity theory has been demonstrated to be an effective lens for understanding how students see themselves with respect to their domain or discipline and its associated community [58, 112, 113]. Previously, Li also noted that just like an individual's identification with a particular ethnic group, social psychological factors influence disciplinary identity [78]. Moreover, disciplinary identity has been shown to be highly predictive of future academic and career behaviors [15, 22, 30, 58, 86, 110].

While disciplinary identity has been studied broadly in engineering, science, and STEM, it has also been studied with respect to more specific fields such as mathematics, physics, chemistry, and biology [15, 27, 30, 43, 44, 56, 57, 61, 80, 94]. Prior work has also examined how learning experiences drive disciplinary identity development and the importance of studying disciplinary identity in order to address equity issues [9]. The framework used in this investigation draws from these prior studies in terms of the sub-constructs that lend to students' computing identities.

While previous research has examined what attracts students to computing programs [1, 3, 25, 59, 76, 118], students continue to develop their affinity identities toward computing within these programs as they navigate experiences with peers, instructors, faculty mentors, and so forth. As such, having a disciplinary identity, such as with computing, is typically considered to be a type of affinity identity that varies from individual to individual even within the same program. In addition, disciplinary affinity identities (such as computing identity) interact with other identities (i.e., with a particular race or ethnicity, and gender).

Although computing identity has been clearly defined in prior work, its attainment is not always straightforward. With the growth in technology access and usage, students have become increasingly familiar with computing and computers. However, this increase does not necessarily translate linearly into rising computing identities. For example, individuals who regularly use

social media, with a larger proportion of women engaging in these activities than men, do not necessarily develop computing identities [47, 125]. In addition, previous work with African American males has demonstrated that just because students may have a passion for computer-related activities (e.g., gaming), this does not necessarily mean it equates to an interest in learning about computing or to the development of computing identity [65]. Therefore, computing identity appears to be the coalescence of several convergent factors and is highly influenced by social perceptions of computing identities [125].

Self-efficacy and/or outcome expectations are considered important to students' choices pertaining to computing. While these factors are insufficient alone to inspire students to select computing, when mediated through interest, students are more likely to choose computing as their major [1]. Additionally, once enrolled in a computing field, interest is considered the most important of the computing identity sub-factors for students' persistence [113]. Further compounding the impact of interest, class level significantly affects pathways mediating recognition and interest.

Recognition from educators, family, or peers about performance/competence in the field can also help to develop confidence in computing abilities and a sense of belonging to the field [62]. For those that are underrepresented in computing, such as women, Black/African American students, and Hispanic/Latinx students, recognition can be a critical piece to combat stereotypes and to overcome "classroom power differentials." Furthermore, receiving recognition and support can be important not only for engagement but also to how students feel within the community, and this becomes a critical component for sustained identity formation.

More work remains to be done on all of the factors that moderate the development of and change in computing identity. Research pertaining to particular groups is especially important to understanding which are the most salient, why, and how we can bolster areas that may be insufficiently developed. In this article, we will examine how undergraduate experiences predict computing identity. By considering academic and programmatic experiences both within and out of the classroom, we hope to gain better insight into which are most relevant for facilitating computing identity development for diverse groups.

2.2 Academic and Programmatic Experiences

Academic and programmatic experiences can be unique to particular fields. Therefore, we examine work on disciplinary experiences in Section 2.2.1, with a particular focus toward computing. In addition, we describe prior literature on the experiences of specific groups. Work related to the experiences of women is presented in Section 2.2.2, and experiences unique to racial and ethnic minorities are presented in Section 2.2.3.

2.2.1 Experiences and Disciplines. Different types of experiences are suggested to be critical in helping to recruit and retain students in various STEM disciplines. Moreover, it has been demonstrated that in the realm of engineering, being an active participant in discourse on engineering disciplines is critical for "enacting a disciplinary identity and communicating affinity" [6, 51, 100]. For this article, we will discuss the experiences that were presented as part of the program for our population of study; such experiences include taking a job in the field or an internship, obtaining help with classwork, participating in clubs, networking, mentoring, receiving academic advising or support, and/or presenting [8, 16, 50, 71, 93, 95, 96, 100, 108, 120].

Mentoring and advising have been shown to be valuable for the development of both undergraduate and graduate students in all fields of study [8, 50, 71, 93, 95, 96]. In computing, role models may include academics, professionals, or other students, and they are considered beneficial for engaging students in the discipline [48]. Mentoring is instrumental not only for career advancement but also for increasing career satisfaction [28]. Moreover, the use of **teaching assistants**

(TAs; near peer mentoring) in undergraduate computing courses is considered effective for both the students enrolled and the TAs themselves [100].

Peer support can be important for computing students' interest, success, retention, and feelings of connectedness and competence [53, 62, 79, 85]. Using pair programming, a technique by which students work together to accomplish a programming task, improves not only enjoyment but also retention [16, 124]. Additionally, sense of belonging is noted as affecting students' perception of their own abilities, perhaps even more so than students' actual performance [120]. Having both academic and non-academic social support and conversations can influence the attitudes students hold toward their abilities.

Furthermore, qualitative analysis of computing students' experiences with work programs and/or internships yielded positive feedback [108]. Students reported not only that they learned a lot from their experience but also that it aided their understanding of computing concepts via real-world application. In addition, there was a tremendous outpouring of encouragement for other students to take advantage of similar opportunities. This type of engagement can impact students' perceptions of their capability and their interest, and subsequently their computing identity.

In summation, although many experiences may have an effect individually, it is still unclear which have the greatest impact on computing identity or their collective impact. It is also unknown if certain experiences are particularly salient for specific groups. Accordingly, we seek to further explore these areas to fill a much-needed gap in understanding.

2.2.2 Experiences for Women. Only 25% of STEM positions are held by women. However, gender differences are even more pronounced in computing fields, where women account for the lowest percentage of the total population, relative to other STEM fields [88, 106]. Although research has been conducted to better understand and remedy the observed underrepresentation of women and to increase female enrollment and persistence, the problem itself appears to be the coalescence of contextual obstacles and perception-based issues [20, 34, 70, 98, 117, 123].

Some of the factors discouraging females from CS include having a lack of early access, role models, and encouragement [20, 38]. In addition, reinforcement of computer science as a male domain has been reported as another potential rationale for diminishing interest [126]. These effects are considered especially problematic when combined with additional deterrents such as the "geek" or "nerd" stereotype and a lack of sense of belonging and confidence [10, 20, 34, 83, 85, 117]. To combat these concerns, early formal and informal exposure can serve to inspire females to consider computing as a field of study [46]. Accordingly, there has been a rise in groups such as Girls Who Code and Black Girls Code and participation in organizations like the Girl Scouts, which seek to empower females and to heighten exposure to computing from an early age [69, 87]. Furthermore, qualitative studies of undergraduate women have demonstrated that for women to choose to major in CS, it is important for them to have friends and other support that encourage their choice to pursue the field [25].

Previous work has shown that gender differences also exist in computing identity, particularly in the area of recognition [40, 62]. Positive recognition in the form of verbal affirmations, praise, or offering more challenging opportunities can help to develop a stronger computing identity—and this is considered especially important for females who may otherwise feel out of place in the field [62]. The experiences that students have can increase identity salience and enhance their sense of belonging in situations where it may otherwise be lacking or meager [62, 64].

When considering the distinction between communal goals (i.e., seeking to better society) and agentic goals (i.e., seeking personal achievement, betterment, and self-promotion), women have been shown to have higher communal goals than men [77]. Also, opportunities for perceived communal affordances (working toward achieving goals) have been linked to an enhanced sense of

belonging in computing. As such, promotion of communal experiences, like volunteering and/or mentoring, are recommended to encourage persistence and improve perceptions of the discipline.

However, just because students may begin with different levels of self-efficacy or sense of belonging or have disparate needs for recognition does not mean that experience cannot impact long-term outcomes for the better. It has been noted that professors should not conflate a lack of exposure with a lack of programming ability [85]. Often women have lower self-efficacy and confidence in computing and tend to perceive the field as more difficult [11, 35, 85]. Yet, this does not equate to lower performance as females have been shown to outperform males on exams [11] and typically attain higher grades overall than their male peers [72]. Furthermore, preparedness is believed to play a role, and female students who initially feel less prepared tend to see a rise over time in confidence, which is attributed to “hard work and discipline” paying off [35].

Since performance itself is clearly not the primary issue explaining differential participation [11, 72], it is important to understand what experiences may encourage women and reduce attrition [62, 85]. When looking at “computing stickiness,” a ratio comparing the number of students that have graduated from a program to the number of students that ever declared a major in that discipline, female students tend to have lower stickiness rates than their male counterparts for all racial/ethnic groups [127]. The only exception to this gender divide occurs with Black males, who have particularly low persistence overall. Furthermore, because computing identity has been shown to be critical to computing students’ persistence [112, 113], this measure is particularly relevant. As such, we will perform a quantitative exploration of specific experiences in computing to elucidate which may have the greatest impact on females’ computing identities.

2.2.3 Experiences and Underrepresented Racial/Ethnic Groups. In general, there are issues engaging minoritized racial and ethnic groups in STEM fields, and often Black/African American and Hispanic/Latinx students are underrepresented [37, 107, 127]. Large disparities have been noted in computing stickiness depending on race/ethnicity and gender [127]. Although Asian male students had a computing stickiness of 49%, Hispanic females and Black male students had some of the lowest computing stickiness at 31% and 33%, respectively. In addition, encouragement plays a role in students’ ability, satisfaction, and likelihood to pursue a career in computing and is considered particularly important for minoritized populations including Blacks and Hispanics [52].

Research on Black and Latino students’ self-efficacy and attitudes has demonstrated that exposure to STEM material is critical to increasing interest and curiosity [84]. Findings suggest that engaging minoritized students in scientific research in urban settings can foster a positive science identity [32, 62, 116]. Furthermore, it can help students to find the science subject matter more accessible and to promote a sense of collective solidarity [31, 32]. Meanwhile, researchers caution that in order to close achievement gaps and dismantle issues of equity, attention must be given to ensure that racially/ethnically underrepresented students receive proper support, encouragement, and recognition in STEM fields, challenging traditional conceptions about “what” and “who” professionals in math or science should be or look like [62, 116, 121].

Moreover, although we will not examine intersectionality in this work, the effects of combining gender and racial identities have been shown to introduce different challenges for students in STEM fields [18, 85, 103, 107]. Undergraduate Latinas and Black women in STEM fields have reported multiple instances of compounded discrimination based on their gender, racial, and ethnic identities [67, 102]. Furthermore, in academic environments, where teamwork is required for laboratory work, assignments, and/or study groups, women of color report feeling excluded [66, 81, 114]. They also report being left out from informal socialization and networking, where information about potential internships, scholarships, and research opportunities is discussed [36, 81, 114]. Such concerns are linked to feelings of isolation, a reduced sense of belonging, and marginalized social identities [68, 102].

While a lack of social support has already been mentioned in STEM fields in general, students in computing have additional constraints [85]. Black women report feelings of cultural isolation and exclusion in computing, and Black males report that identification with computing is not part of the social norms within their peer group [18, 65]. Such “disidentification” is considered a deterrent both for academic outcomes and for professional growth [65]. In addition, interviews with Latina students in computing pointed to a cultural component unique to this population—the difference between individualist versus collectivist mindsets [102]. One of the subjects mentioned that often computing fields lend to antisocial behaviors and that typically students work alone. This particular finding not only has impacts for sense of belonging but also highlights a key difference in cultural backgrounds between Latinx students and others. Latin cultures tend to be more group oriented and to place more emphasis on the community and cooperation, a psychosocial construct known as collectivism [4]. Thus, for Latinx students, being part of a major where others may prefer to work alone could impact performance and retention. To combat such feelings of dissonance, peer support can be a tremendously positive influence [85]. Students in computing at historically Black colleges and universities reported higher levels of social support, greater outcome expectations, and elevated academic and coping self-efficacy than students at predominantly White institutions [75].

Given that different social groups have varied perspectives and influences, consideration must be given to the unique experiences that contribute to students’ identities. In this work we consider not only experiences that affect computing students but also the potential interaction between belonging to an underrepresented group and computing identity. Only through increased understanding and ongoing efforts can we hope to achieve more equitable representation in computing.

3 OUR WORK

This study is framed using disciplinary identity theory as the primary framework. However, we also applied aspects of Gee’s Affinity-Identity to explore the educational development of computing students and to understand how shared experiences impact their disciplinary identity. Specifically, the **research questions (RQs)** for this work are:

- RQ1: How well do the questions for computing identity correspond to the theorized sub-constructs?
- RQ2: How do academic and program experiences in computing predict computing identity?
- RQ3: How are the effects different for females and underrepresented racial/ethnic groups (in this case, Black/African American and Hispanic/Latinx students)?
- RQ4: What is the difference in the likelihood of having significant experiences for females and underrepresented racial/ethnic groups (Black/African American and Hispanic/Latinx) as compared to the rest of the population?

To address these questions, we conducted a quantitative survey of students’ experiences and identities in computing programs at three large universities. First, we analyzed the data using a **confirmatory factor analysis (CFA)**. Then, we built a regression model using backward block elimination to look at how different experiences predict computing identity development. Given critical issues related to the underrepresentation of certain groups in computing, exploring the sources of disparities and how to remedy the situation requires increased understanding. As such, we also examined the interaction effects of experiences and identifying as female, Black/African American, and Hispanic/Latinx. Finally, Wilcoxon tests were run to look at differences in frequency of the significant experiences that emerged in the regression for those who identified as female, Black/African American, and Hispanic/Latinx.

Table 1. Academic Standing and Gender Identity of Participants

Academic Standing (Year)					Gender Identity		
<i>1st</i>	<i>2nd</i>	<i>3rd</i>	<i>4th</i>	<i>Past 4th</i>	<i>Male</i>	<i>Female</i>	<i>Other*</i>
5.6%	17.5%	32.9%	26.9%	5.6%	77.6%	21.0%	1.4%

*Reported as transgender, agender, a gender not listed.

4 METHODOLOGY

We describe our survey instrument in Section 4.1. In Section 4.2 we provide the demographics of our population. Then, the analytic approach utilized to address the RQs is further detailed in Section 4.3.

4.1 Survey Development and Administration

After the IRB approved, a survey was administered to computing students at three large, metropolitan public universities in Florida via Qualtrics. The survey instrument consisted of 39 questions in total, which included demographic information, questions about the students' academic standing (year in school, major, and GPA), and inquiries into the students' experiences, persistence, and interests. Moreover, questions were asked about the students' support network and home life (such as working outside the home, if they are caring for others, etc.) and educational history. The survey questions assessed are presented in Appendix A.

These questions were based on established instruments from the fields of engineering and science [17, 58]. To substantiate that the measures were relevant to computing students, and to assess the face, content, and construct validity of the survey, we ran a pilot study [112]. Face validity refers to the extent the questions from our survey covered the concepts they were intended to measure [60]. We verified that the questions indeed matched the target topics, including the sub-constructs of computing identity [112]. We also tested that the academic experiences proposed were applicable to computing students. Content and construct validation were also performed by Taheri et al. [112]. Content validity considers how well a measure may consider all aspects of a given construct [54]. Meanwhile, construct validity is used to determine the extent that questions asked cover an abstraction or phenomenon of interest, which in our case was computing identity [26]. Taheri et al. applied CFA to ensure adequate coverage for the different dimensions of the sub-constructs for computing identity and used structural equation modeling to provide an overview of the relationships [112, 113].

The initial pilot and analyses confirmed the questions were pertinent to computing students and verified the construct. However, this prior research merely determined that the experiences were appropriate and selected, but it did not explore their frequencies or their correlation with computing identity. In this study, we focus on the individual experiences chosen to determine their impact on students' computing identities. While the questions pertaining to computing identity were the same as the work previously conducted, this was a survey administered in another year, with a new population of students. As such, we also ran a CFA on the data from our present population to further confirm the construct validity and reliability. Also, an analysis of the individual sub-constructs against the combined measure was run to demonstrate the criterion validity, a comparison utilized to illustrate the extent to which each predicted future outcomes.

4.2 Demographics

Our sample consisted of 1,654 students from CE, CS, and IT. Information about the students' academic standing and their gender identity is presented in Table 1. We detail the racial and ethnic affiliations reported in Table 2.

Table 2. Racial/Ethnic Identity of Participants

Racial/Ethnic Affiliation							
<i>White</i>	<i>Black/ African American</i>	<i>Asian</i>	<i>Native Hawaiian/ Pacific Islander</i>	<i>American Indian/ Alaskan Native</i>	<i>Hispanic, Latinx, or Spanish Origin</i>	<i>Middle Eastern/ North African</i>	<i>Another Race Not Listed</i>
44.6%	11.9%	16.4%	1.0%	1.4%	35.9%	3.1%	2.2%

Table 3. The Survey Questions Utilized to Build the Latent Variables That Define Computing Identity

Recognition	Interest	Competence/ Performance	Sense of Belonging <i>With respect to the computing community, to what extent do you...</i>
Extent your family sees you as an exemplary student in computing fields	Topics in computing excite my curiosity	I am confident I can understand computing	feel like you are part of the community
Extent other students see you as an exemplary student in computing fields	Computer programming is interesting to me	I can do well on computing tasks (e.g., programming and setting up servers)	feel valued and respected
Extent your teachers see you as an exemplary student in computing fields	I enjoy learning about computing	I understand concepts underlying computer processes	feel you can share your thoughts/ideas
	I like to know what is going on in computing		feel you can be heard

4.3 Analytics

Statistical analyses were conducted using R (version 3.6.1) in RStudio (version 1.1.456). A CFA was run to confirm that particular questions mapped onto the theorized computing identity sub-constructs. The resulting latent variables for the sub-constructs were defined according to the items denoted in Table 3. These items were averaged to create proxies for each sub-construct, which were then combined to represent an overall proxy measure for computing identity. Computing identity has been shown to be critical to computing students’ persistence [112, 113], making it an important outcome measure. Accordingly, this proxy became the dependent variable in the regression model with independent variables encapsulating demographics/background variables (controls) and experiential variables in computing programs. Effects of institution and major were controlled.

Regression is a statistical method utilized to establish relationships between a dependent variable and one (or more) independent variable(s) and to explore their interactions [39, 109]. We used blocked regression, first applying only the controls in isolation. Then, in the second block, we added in the predictor variables for specific computing experiences.

Each predictor represents a student’s reporting of a particular computing experience (see precise question wording in Appendix A). While experiences may appear grouped, there was no a priori grouping or categorization for the experiences; we merely present similar results together for ease of making sense of them conceptually. We also included interaction effects between experiences and gender/underrepresented racial/ethnic groups to assess whether experiences had a different effect on computing identity depending on group affiliation. Once significant experiential variables were identified, the final analytic approach was to use Wilcoxon rank sum tests to examine the likelihood of female and underrepresented racial/ethnic groups reporting that they had these critical experiences at different rates when compared to others in their programs.

Table 4. Computing Identity Construct Factor Loadings

Latent Variable	Indicator Variable	Standardized Factor Loading (i.e., std. all)	SE	Item Reliability R^2 (>0.50)	Construct Reliability (>0.70)	Average Variance Extracted (>0.50)
Recognition	Family	0.65***	0	0.43	0.85	0.65
	Other students	0.88***	0	0.78		
	Computing teachers	0.87***	0	0.75		
Interest	Computing excites curiosity	0.87***	0	0.75	0.92	0.74
	Programming is interesting	0.76***	0	0.58		
	I enjoy learning about	0.93***	0	0.86		
	I like to know...going on...	0.88***	0	0.77		
Competence/ Performance	I understand computing	0.80***	0	0.64	0.83	0.62
	I can do well on tasks	0.77***	0	0.59		
	I understand concepts	0.79***	0	0.62		
Sense of Belonging	Feel part of the community	0.79***	0	0.62	0.90	0.70
	Feel valued and respected	0.85***	0	0.72		
	Feel you can share	0.85***	0	0.73		
	Feel you can be heard	0.86***	0	0.74		

*** $p < 0.001$.

5 RESULTS

5.1 Confirmatory Factor Analysis and Criterion Validity

Prior literature has set a precedence for using computing identity as a predictor of career outcomes [80]. As mentioned, structural equation modeling was also previously conducted to demonstrate that the sub-constructs are valid to use in modeling computing identity [112, 113]. However, to reconfirm the work of others and to further expand upon the knowledge for use within our context since the survey was with a different sample, we ran a CFA and a test for criterion-related validity.

CFA was used to test how well the questions from our survey aligned with computing identity, to assess its construct validity. Table 4 describes how the 14 questions from Table 3 loaded onto the four theorized factors. The four-factor design for computing identity was previously described in other computing identity work [112, 113]. All of the standardized factor loadings are above the accepted 0.4 threshold [115]. Although our χ^2 was significant ($p < 0.001$), since our sample was so large, we used other methods to determine the fit of the measures for our model. The Root Mean Square Error of Approximation was 0.078, which is less than 0.08, and implies an acceptable fit [104]. The Comparative Fit Index was 0.959, which is above the acceptable model fit threshold (≥ 0.90) and indicates that 95.9% of the co-variation in the data can be reproduced by our model [41]. Likewise, the Relative Fit Index (0.939), Normed Fit Index (0.955), and Non-Normed Fit Index (0.944) were all above the “good fit” threshold as well. Contrarily, for the **Standardized Root Mean Square Residual (SRMR)**, the smaller the value, the better the fit, and a value of 0 suggests a “perfect fit.” In our analysis, the model’s SRMR was 0.036, which is less than the 0.05 threshold required to denote a “good fit.”

Prior to combining the sub-constructs into a proxy for subsequent analyses, we examined how predictive each individual sub-construct was for a long-term outcome (related to disciplinary identity such as persistence) compared to the combined proxy. Specifically, the long-term outcome we used was the likelihood that the student would finish a bachelor’s degree in their current major (precise wording shown in Appendix A). The estimate for interest alone in predicting their likelihood of degree completion was 0.39. In terms of the other sub-constructs, the estimate for

recognition was 0.39, it was 0.46 for competence and performance, and it was 0.28 for sense of belonging. Comparatively, using our combined measure of computing identity as a predictor for their likelihood of degree completion yielded an estimate of 0.58. Therefore, we operationalize this combined measure of computing identity for our outcome, based both on the prior literature and on the higher predictive ability of our proxy for persistence. This also lends to the criterion-related validity of the proxy.

5.2 Regression Models

We created a regression model using the computing identity proxy as the dependent variable and undergraduate computing experiences as well as demographic/background controls as our independent variables. Then, we assessed the interactions to determine what experiences were most salient for women, Black/African American students, and Hispanic/Latinx students' computing identity.

The regression model predicting computing identity is described in Table 5. Our goal was to first control for demographics and background variables to minimize the effect of confounding variables, and then to test the effects of undergraduate computing experiences. Block I shows the control set of variables, and then in Block II we added in the experiential variables to explore the role of each, as well as interaction effects with gender and race/ethnicity. It should be emphasized that although we present the control variables, experiential variables, and interactions as distinct sections in Block II, the model itself is a single model. The experiential variables with a significant effect on computing identity pertain to the entire population, whereas the interactions focus solely on marginalized groups. We observed that the adjusted R^2 for our control block was 26.81%, which, with the addition of experiential variables, rose to 35.74%. This denotes an 8.93% increase in the variance explained from the experiential variables that were added.

While we present the standardized β coefficients in Table 5, we also calculated the semi-partial correlations. All were less than 0.1 except for the friends in computing variable, which was 0.15. Thus, with the exception of this variable, the effect sizes were all small based on Cohen's correlation heuristic [23].

In addition, to determine if multicollinearity was an issue, we ran variance inflation factor statistics on our models. Typically the threshold is greater than 5 [2, 82]. However, for all the variables, all the statistics were less than 1.5, suggesting that multicollinearity is not a substantial issue.

5.3 Wilcoxon Rank Sum Tests

To compare the likelihood of women, Black/African American students, and Hispanic/Latinx students reporting significant experiences identified in the regression relative to other groups in the data, we applied Wilcoxon rank sum tests. This test allowed us to compare groups (e.g., female versus non-female) on variables that had various distributions including binary variables coded as "yes" they had a certain computing experience or "no" they did not. Table 6 describes those experiences that occur at significantly different likelihoods for each population.

6 DISCUSSION

6.1 RQ1: How Well Do the Questions for Computing Identity Correspond to the Theorized Sub-constructs?

Consistent with the work of others [113], we found a strong correspondence between the four sub-constructs and computing identity. The results of the CFA confirm that the reliability of individual questions and the overall reliability are within acceptable ranges [29, 115]. Furthermore, the CFA

Table 5. Regression Models Predicting Computing Identity Measure with Gender Ethnicity Interactions

<i>Parameters</i>	Models (N = 1,654)							
	<i>I</i>				<i>II</i>			
	Estimate	Sig.	SE	β	Estimate	Sig.	SE	β
Control Variables								
(Intercept)	1.90	***	0.15	0.00	2.00	***	0.14	0.00
Institution (2)	−0.07	ns	0.04	−0.05	−0.04	ns	0.04	−0.03
Institution (3)	0.01	ns	0.02	0.01	0.02	ns	0.05	0.01
Majoring in IT	0.02	ns	0.04	0.01	0.04	ns	0.04	0.02
Majoring in CE	0.07	ns	0.04	0.04	0.05	ns	0.04	0.03
Other Major	−0.47	***	0.04	−0.25	−0.40	***	0.04	−0.21
GPA in Computing	0.23	***	0.03	0.17	0.19	***	0.03	0.13
Grade in High School Math	0.07	**	0.02	0.07	0.07	**	0.02	0.06
Grade in College Math	0.07	**	0.02	0.07	0.06	**	0.02	0.06
Asian	−0.10	*	0.04	−0.05	−0.11	**	0.04	−0.06
Hispanic/Latinx	0.05	ns	0.03	0.03	−0.03	ns	0.06	−0.02
Middle Eastern	−0.18	*	0.09	−0.04	−0.14	ns	0.08	−0.03
Another Race	−0.30	**	0.10	−0.06	−0.31	**	0.10	−0.06
Female	−0.11	**	0.04	−0.07	−0.15	***	0.04	−0.09
Supportive Home	0.19	***	0.02	0.27	0.16	***	0.01	0.23
Hours Working outside Home	0.01	***	0.00	0.14	0.01	***	0.00	0.09
Has a Health Issue	−0.15	**	0.05	−0.06	−0.17	**	0.05	−0.07
Other Life Factor	−0.18	**	0.07	−0.06	−0.17	**	0.06	−0.06
Experiential Variables								
Research Experience					0.09	*	0.04	0.04
Having a Job					0.11	**	0.04	0.07
Mentoring Others					0.16	***	0.04	0.09
Being Mentored					−0.09	**	0.03	−0.06
Being in Club(s)					0.08	*	0.03	0.05
Presenting (Not Classwork)					0.09	*	0.04	0.05
Networking with Industry					0.08	*	0.04	0.05
Students in Class Help on Classwork					−0.08	*	0.04	−0.05
Advisors Help on Classwork					0.11	*	0.05	0.04
Others Help on Classwork					0.02	*	0.01	0.05
Academic Advice from TAs					0.04	ns	0.04	0.03
Academic Advice from Industry					0.08	ns	0.04	0.05
Friends in Computing					0.03	***	0.00	0.15
Interactions								
Female <i>and</i> Academic Advice from TAs					0.20	*	0.08	0.06
Hispanic/Latinx <i>and</i> Students in Class Help on Classwork					0.16	*	0.07	0.11
Hispanic/Latinx <i>and</i> Academic Advice from Industry					−0.18	**	0.07	−0.07

*p < 0.05. **p < 0.01. ***p < 0.00.

Note. ns = not significant; TAs = teaching assistants.

results support the construct validity of the measures, and the predictive ability of the computing identity proxy for the likelihood of persistence supports the criterion-related validity of the measures. These results suggest not only that the four sub-constructs (interest, sense of belonging, recognition, and competence/performance) in the theoretical framework are well aligned with

Table 6. Likelihood of Experiences for Groups Underrepresented in Computing

Academic and Programmatic Experience	Non-Female Female			Non-HL HL			Non-Black/AA Black/AA		
	p-Value	Mean	Mean	p-Value	Mean	Mean	p-Value	Mean	Mean
Being in Club(s)	0.00	0.28	0.36						
Presenting (Not Classwork)	0.02	0.37	0.32						
Networking with Industry	0.02	0.18	0.24						
Others Help on Classwork				0.00	1	1.24			
Friends in Computing							0.00	5.16	4.39

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

the measures on the survey but also the robustness of the overall proxy for computing identity. As such, this further confirms the validity of the framework, as shown in other work [80, 112, 113].

6.2 RQ2: How Do Academic and Program Experiences in Computing Predict Computing Identity?

The next research question examines the role of different experiences on computing identity. As demonstrated in the results of Table 5, quite a few experiences have a significant effect on computing identity including research experience, job experience, mentoring others, being mentored, club participation, presenting, networking, working on classwork (with students in the class, obtaining help from advisors, working with others not in the class), and having friends in computing. All of these effects are positive with the exception of the experience of being mentored and working on classwork with students in class, which are negative.

Before we begin discussing some of the major findings, we would like to emphasize that although the majority of individual effects may be small (based on Cohen's heuristics [23]), cumulatively they can have a larger impact on an individual's identity. Prior research has reported that similar small effects, such as experiences with one class, within complex educational systems collectively have larger effects on disciplinary identity [63]. Also, engaging in a combination of experiences could contribute to a student's broader impression of the field. Previously Jackson and Seiler described how experiences may accumulate to "thicken" and reinforce identity, a concept they refer to as "momentum" [64]. It is this notion of possessing momentum based on accumulated individual experiences that contributes to a growing (or eroding) disciplinary identity that propels the discussion to follow. Although we did not formally group or categorize students' experiences, we will review conceptually related topics together below.

Having professional experience, either with research or from a job, shows a positive impact on computing identity. More specifically, students who have had research experience have a β of 0.04, and having a job has a slightly larger β of 0.07. These effects complement each other, as well as qualitative work in the field, in which researchers have previously solicited feedback from computing students upon completion of work programs/internships and found that students view such experiences as beneficial to their learning and understanding [108]. Furthermore, this qualitative work concluded that overwhelmingly, students encourage other computing students to seek similar opportunities, a finding our results support in terms of fostering the development of a stronger computing identity.

Mentoring other students and being mentored also affect computing identity. While mentoring others is positively significant with a β of 0.09, being mentored is actually inversely related, with a β of -0.06. These relationships are not completely surprising as we postulate that receiving

mentoring may make students feel less capable for requiring support. It may also indicate a lack of training and empathy of students who mentor others. If they have a deficit model when mentoring, they may inadvertently position the students they are mentoring as deficient. Contrarily, mentoring others could help a student to solidify their own knowledge and understanding, and may make them feel more confident in their abilities to teach and problem solve as they explain concepts and assist others. This theory is further grounded in the works of others, who have demonstrated that mentoring peers in computing has a positive effect for the student doing the mentoring when using fellow undergraduate students as section leaders in introductory programming courses [100]. Antithetical to our own quantitative results, in the study with the section leaders, they found it was beneficial for the students receiving the mentoring. It is important to note that in the section leader scenario, students were assigned a leader as part of their regular course, and thus, the students did not directly request help—it was assigned to them. As such, it is possible there is a stigma associated with seeking out mentoring or being identified as a student who requires more mentoring than other students. However, further qualitative analysis is required to examine this theory.

In line with the results that demonstrate a positive relationship between being a mentor and computing identity, likewise, presenting on computing topics also shows a significant correspondence with computing identity, with a β of 0.05. We hypothesize that similar to mentoring, the reason for this is that it further allows a student to solidify topics in their understanding and demonstrate their capability in the field as they share with a wider audience. This provides opportunities for recognition that are central to identity development.

Also highly significant are having friends in computing ($\beta = 0.15$), networking ($\beta = 0.05$), and being part of a club ($\beta = 0.05$), which supports previous work that has demonstrated the importance of social support [91, 100]. Participation in clubs and networking allow computing students to engage with other like-minded individuals and grow a sense of belonging, which is important for the identity development of college students [56, 112]. Moreover, as problems or issues arise in their programs, it may be more comfortable to gain support from peers who understand the rigors of the program and field and face shared challenges. For students who are minoritized in STEM fields already, qualitative studies have demonstrated that having peer support can be particularly important [91].

In addition to the significant experiences described, we would also like to draw attention to some of those that were not, from the full list that was assessed in Appendix A. The absence of certain experiences makes a compelling case that program implementation could be reworked or redesigned to better utilize these experiences for the benefit of computing students. For example, while having job or research experiences did predict computing identity, shadowing experiences did not. Therefore, it may be less important to observe others and more important to actually engage in computing work. Participation has been shown to be important for CS students' development, particularly with regard to creating things (e.g., games, apps) and problem solving [97]. Accordingly, shadowing experiences may benefit from the inclusion of hands-on activities or involvement. Likewise, while being part of a computing group, club, and so forth was significant, neither attending symposia or other computing events nor attending social events organized by the department were. Therefore, it is not sufficient merely to gather students, but there may be aspects of professional and identity development attained from computing groups and clubs where more meaningful experiences may transpire that influence feelings of recognition and sense of belonging. Together, these results point to the importance of active forms of participation versus more passive forms. Through additional research, administrators could explore what types of events and activities organizations on campus offer that students consider the most beneficial. Whether this

entails engaging with new technologies or offering workshops to develop resumes, universities could refocus efforts to enhance student outcomes. Alternatively, since presenting work to other students (not classwork) was also a significant experience, another way to improve the impact of departmental events or symposia could be increasing formal and informal opportunities for students to demonstrate their findings and projects to others.

6.3 RQ3: How Are the Effects Different for Females and Underrepresented Racial/Ethnic Groups (in this Case, Black/African American and Hispanic/Latinx Students)?

In general, females have a significantly lower computing identity than non-females, as demonstrated in Table 5. This is consistent with the work of others [40]. While a number of factors may be responsible (as described previously in Section 2.2.2), further qualitative analysis is required to understand the underlying causation.

Additionally, we examined the interactions between experiences and identification as being female or belonging to an underrepresented racial/ethnic group to assess whether certain experiences may have differential effects on computing identity for each group. The significant interactions are also presented in Table 5. Although we examined the interactions for women, Black/African American students, and Hispanic/Latinx students, there was no significant main effect or interactions for those who identify as Black/African American.

When examining interactions for females with experiences, we observed that compared to the baseline, getting advice/help in their academic program/career from teaching assistants or **learning assistants (LAs)** significantly boosts females' computing identity more than it does for non-females, as illustrated in Figure 2. This aligns with prior reports that undergraduate females in computer science are more likely than males to seek guidance from TAs [73]. One potential explanation is that teaching or learning assistants may be viewed as sources of guidance that help females to develop their own confidence and preparedness on computing topics [100]. In addition, LAs and TAs are in more of an authority position than classmates, so receiving advice from them may serve as recognition of their capability and competence, particularly since LAs and TAs do not typically play an advising role. Gender effects of mentors, and the extent of mentoring, has been shown to impact self-efficacy in computing [45, 85], although we were unable to find prior work considering the impact specifically of TAs on females in computing programs. However, this would pose an interesting topic for future research, and it could also be worthwhile to consider a comparison of the effects of students working with either same-gender or cross-gender TAs.

For Hispanic/Latinx students, there were two major interactions. First, Hispanic/Latinx students who reported working with other students in their course on classwork had a significant increase in computing identity relative to other groups, as demonstrated in Figure 3. It should be noted that this type of peer collaboration experience was significant for Hispanic/Latinx students, unlike other forms of classwork assistance a student may receive, such as that which they get outside the class from students, TAs, LAs, faculty/instructors, advisors, or other sources of guidance. This interaction further reinforces prior literature that has demonstrated that peer support is very important for Latinx college students [101].

The other experiences that seem to be unique for Hispanic/Latinx students pertain to academic advising/advice. Receiving support from the academic and non-academic community can affect students' belief in their own abilities and can affect their resiliency in the face of adversity [120]. However, as shown in Figure 4, we observe a negative interaction between seeking advising/help in their academic program/career from industry professionals for their computing identity. One possible explanation for this is that the way industry professionals interact with these students during technical interviews, jobs, or other situations places high expectations, often unreasonably

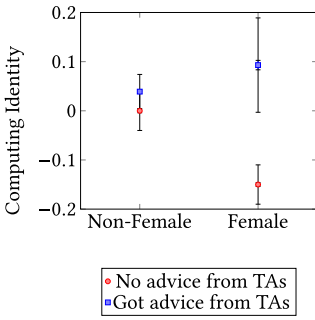


Fig. 2. Interaction effect: Female and Academic advice from teaching assistants (TAs).

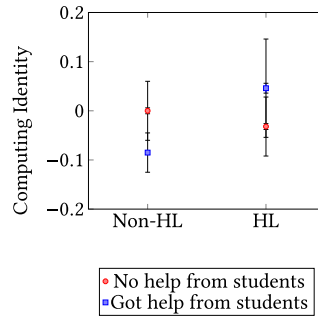


Fig. 3. Interaction effect: Hispanic/Latinx (HL) and Students in class help on classwork.

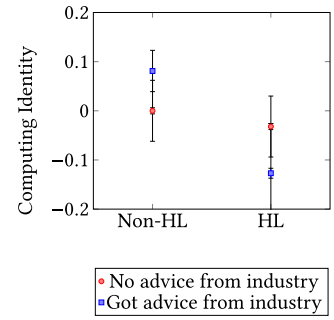


Fig. 4. Interaction effect: Hispanic/Latinx (HL) and Academic advice from industry.

so, which may make them feel less capable or competent in computing. It has been shown that students in general struggle to succeed at technical interviews while seeking employment, with a lack of good preparation within programs in the areas of project experience, oral communication, and problem solving [99]. In addition, technical interviews have been reported to cause anxiety and frustration [7]. Doing poorly or receiving criticism in these areas could be an off-putting factor that is particularly discouraging for Hispanic/Latinx students, leading to feelings of disappointment, discouragement, and lower computing identity. To further assess this, it would be beneficial to inquire about the types of industry interactions students experience, so that its impact can be better understood.

6.4 RQ4: What Is the Difference in the Likelihood of Having Significant Experiences for Females and Underrepresented Racial/Ethnic Groups (Black/African American and Hispanic/Latinx) as Compared to the Rest of the Population?

In addition to the interaction effects previously described, we also observed several significant differences in the likelihood of certain experiences (from Table 5) when comparing underrepresented groups to those not underrepresented in computing (illustrated in Table 6). Comparing females to non-females, 36% of women report being part of a club at their institution, as opposed to only 28% of men. In addition, females are more likely than males to engage in networking, with 24% of females reporting this experience as opposed to only 18% of males. Both participation in clubs and networking are important because they offer opportunities for interaction with others in the field. This may be particularly salient for women since peer support and having positive role models have been found to be critical for the retention of women in computing [24, 25]. These results are encouraging but also show that these experiences should be further promoted, particularly for women, to increase persistence in the discipline.

Contrary to the other significant experiences, males are more likely to present (with 37% of males reporting this experience) than females (with only 32% reporting this experience). However, it is unclear what the root cause for this gender difference is, and if it is the result of women having fewer opportunities to speak, personal choices to avoid presenting, women taking less of a lead in group presentations, or some other factor. Moreover, we do not examine whether these presentations were for a class or academic/professional conference. Therefore, going forward,

these items should be considered with a qualitative analysis to better understand the underlying mechanisms that contribute to the observed difference.

For Hispanic/Latinx students, working with students in class (Table 5: positive interaction) and outside of class (Table 5: main effect) had a positive effect on their computing identity. In terms of frequencies, it is heartening to observe that Hispanic/Latinx students also report experiencing classwork with others significantly more than the rest of the population. It should be clarified that this question on the survey addressed how many people students work with. The average score of 1.24 for Hispanic/Latinx students indicates that they work with slightly more than one person on average, a finding that complements prior literature on the importance of relationships and communal environments for Hispanic/Latinx students [49, 101].

Based on frequency, Black/African American students report having fewer friends in computing (an average of 4.39 friends) than non-Black/African American students (an average of 5.16). Previous qualitative work has delineated that Black participants report feeling more culturally isolated and excluded [18]. Moreover, Charleston et al. suggest there are differences in the approach of Black males and females to developing relationships in computing. This work found that Black males place a stronger emphasis on developing friendships with White males, whereas Black females have a lower inclination. This is important because, as we described, having friends in computing is a significant predictor of computing identity.

7 LIMITATIONS

Given the expanse of literature describing the importance of certain experiences in computing, it should be noted that findings from this investigation are limited in several ways. First, we only employ quantitative analysis. Thus, although this may provide numerical confirmation of the effects observed by others, we cannot be certain about what the observed relationships mean without further examination. To uncover explanations of these numbers and to gain more information about how they interrelate, qualitative exploration is necessary.

Next, in this research we only examined the impact of experiences on the combined construct of computing identity. However, specific experiences may contribute differentially to the individual components—sense of belonging, interest, recognition, or competence/performance. Such analysis could provide valuable insight into the nuances of these relationships and would be interesting for future research.

Moreover, we do not consider the intersectionality of the different groups in this study. Consequently, although we may look at females and at Blacks/African American students, in this work we do not consider women who are also African American, which may limit our understanding of relationships of differential importance for intersecting identities. While that was beyond the scope of the current work, it would be worthwhile to pursue as it could provide more insight into the perceptions and experiences of computing students in more intersectional ways.

In addition, as with any study, we are limited by the types and levels of experience that we were able to survey students about. Future work should delve more into particular aspects of the experiences (e.g., the identities of who students worked with, the nature of advice given) as well as examine experiences at other levels (e.g., K-12, workplace). While it is valuable to understand the effect of experiences in computing programs, it is important to note that the experiential variables we focused on only explained a third of the variance compared to the control variables. As such, other factors like prior academics, background, and demographics may also contribute. Finally, it should be noted that we set our threshold for statistical significance at 0.05; thus, there may be significant results that emerge by chance. However, this is an exploratory study, and we triangulate as much as possible with the literature for experiences that were found to be significant.

8 CONCLUSION AND IMPLICATIONS FOR FUTURE RESEARCH

Clearly computing identity is a complex topic, and attention should be paid to consider the factors that attract or repel different groups. These results have broader implications for computing education and for research as well. The current inquiry provides empirical evidence that individual academic and programmatic experiences play an important role in predicting computing identity. Moreover, quantifying how specific computing experiences shape disciplinary identity has the potential to elucidate specific areas of focus to improve long-term outcomes. For example, consideration of how senior students talk to more junior students, and how industry professionals approach and respond to candidates and students, could be critical given that these play such an essential role in the development of computing identity, particularly for groups that are already underrepresented in computing. Furthermore, offering social support through clubs or mentoring, and opportunities like research, job internships, and presentations are crucial to consider for strengthening computing identity.

In the future, it would be interesting to further expand the types of experiences examined in terms of the impact on students' computing identity. Moreover, qualitative exploration could result in new measures not previously considered and could provide insight into the nuances of the relationships described in this work. Since it appears that academic advising/help from industry professionals has a negative effect on computing identity for Hispanic/Latinx students, it is also imperative to further explore the dynamics underlying the observed effect and to examine our hypothesis that technical interviews may be responsible. Likewise, assessment of what types of presentations are being given and their purpose, as well as trying to understand why women are presenting less (if it is opportunity related, a personal choice, or a combination), would provide valuable insight that could translate into possible solutions through mentoring and greater opportunities for professional development.

Through evaluation of the individual factors that contribute to the development of computing identity for different groups, we seek to ameliorate current practices and approaches to empower all students. Understanding the complexity of how students' other social identities relate to their computing program experiences and computing identities could be valuable for administrators/faculty. Giving consideration to which opportunities and experiences are relevant and productive to improving engagement and equity in computing fields' epistemic practices can ultimately serve to benefit both students and educators in the long term.

APPENDIX

A SURVEY INSTRUMENT

We have included the questions from the survey that are relevant for this research. First, we include those questions used to construct computing identity in Table 7. Then, we include the questions used to construct the control block in Table 8, and then experiential questions assessed in Table 9.

Table 7. Questions and Responses Used to Determine Computing Identity

Question Asked	Response Options	Response Scale
Rate the following statements as they apply to you:	• To what extent do you see yourself as an exemplary student in computing fields • To what extent does your family see you as an exemplary student in computing fields • To what extent do other students see you as an exemplary student in computing fields • To what extent do your teachers see you as an exemplary student in computing fields • I am confident I can understand computing • Others ask me for help with computers • Others ask me for help with software (applications/programs) • I can do well on computing tasks (e.g., programming and setting up servers) • I understand concepts underlying computer processes • Topics in computing excite my curiosity • Computer programming is interesting to me • I enjoy learning about computing • I like to know what is going on in computing	Likert Scale (5 points): 0 = not at all to 10 = very much
With respect to the computing community, to what extent do you...	• feel like you are part of the community • feel valued and respected • feel alone or isolated • feel you can share your thoughts/ideas • feel you can be heard • feel inadequate as a member	Likert Scale (5 points): 0 = not at all to 10 = very much

Table 8. Questions and Responses Used for Control Block

Question Asked	Response Options	Response Scale
What institution are you enrolled in?	Institution names not shown for anonymization	Select One
What is your major (or intended major)?	Computer Science, Information Technology, Computer Engineering, Other	Select One
What is your average GPA in your computing courses?	<1.0, 1.0–1.49, 1.5–1.99, 2.0–2.49, 2.5–2.99, 3.0–3.49, 3.5–4.0, >4.0	Select One
What grade did you receive in your highest high school mathematics course?	A+, A, A-, B+, B, B-, C+, C, C-, D, F	Select One
What grade did you receive in your highest college/university mathematics course?	A+, A, A-, B+, B, B-, C+, C, C-, D, F	Select One
How supportive is your home environment toward computing?		Likert Scale (5 points): Not at all supportive to Extremely supportive
How many hours do you work outside the home each week?	0, 1–5, 6–10, 11–15, 16–20, More than 20	Select One
Which of the following apply to your day-to-day life? Mark all that apply	• Caring for a child (e.g., sibling, your own child) • Caring for an adult (e.g., grandparent) • Personal recurring health problem (not including common illnesses like a cold or flu) • Other (Text Entry)	Select All, with Text Entry
With which racial and ethnic group(s) do you identify?	• American Indian or Alaska Native • Asian • Black or African American • Hispanic, Latinx, or Spanish origin • Middle Eastern or North African • Native Hawaiian or Other Pacific Islander • White • Another race or ethnicity not listed above	Select All
How do you describe your gender identity?	• Female • Male • Agender • Transgender • A gender not listed • Text entry	Select One, with Text Entry

Table 9. Questions and Responses Used to Assess Academic and Programmatic Experiences

Question Asked	Response Options	Response Scale
Which of the following experiences have you had at your institution with respect to computing?	• Industry internship • Research experience • Shadowing experience • Job experience • Job offers • Tutoring experience, being a learning assistant • Mentoring another student(s) • Being mentored by another student(s) • Being part of a computing group, club, etc. • Attending symposia or other computing events • Attending social events organized by the department • Presenting work to other students (not classwork) • Networking with industry and other professionals • Interacting with students in different years(s) (lower year or more senior students)	Select All
Which of the following people, if any, have helped you with classwork? Mark all that apply:	• Students in the class • Students outside the class who have taken it before • Teaching or learning assistants • Faculty/instructors • Advisors • Other	Select All
Who do you typically work with for classwork (when you have a choice)?	• By myself • 1–2 other students • 3–4 other students • More than 5 other students	Select One
Outside of classwork, which of the following people, if any, have advised or helped you in your academic program/career? Mark all that apply.	• Students in your year • Students more senior to you • Teaching or learning assistants • Faculty/instructors • Advisors • Industry professionals • Other	Select All
Outside of classwork, which of the following people, if any, have advised or helped you in your personal/social life? Mark all that apply.	• Students in your year • Students more senior to you • Teaching or learning assistants • Faculty/instructors • Advisors • Industry professionals • Other	Select All
How many friends do you have in computing?	0, 1–2, 3–4, 5–6, 7–8, 9–10, More than 10	Select one

B R CODE FOR ANALYSIS

Code can be made available upon request.

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