

The Impact of Technical Interviews, and other Professional and Cultural Experiences on Students' Computing Identity

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ABSTRACT

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

CCS CONCEPTS

• **Social and professional topics** → **Computing education**.

KEYWORDS

Computing identity, hiring in computing, diversity in computing

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1 INTRODUCTION

Companies looking to hire for computing positions frequently evaluate job candidates' technical proficiency using problem solving and coding tests [4]. Although students may have completed coursework about the fundamentals of programming and algorithmic efficiency, answering these questions on the spot while also speaking their thought process aloud can be cognitively challenging and stressful [2, 5]. Technical interviews (TIs) are considered a major hurdle for students in computing looking to obtain a position in industry, and also for companies trying to grow and to build diverse teams [4, 5]. Recent computer science graduates are often cited as lacking in technical abilities, communication skills, and other aspects of professionalism [31, 34, 40]. Given that there is already an insufficient amount of computing graduates to meet industry needs — and a dearth of women, Black/African American, and Hispanic/Latinx students — further deterring these populations at any stage is problematic [13, 29, 35].

Certain experiences are considered beneficial to promoting disciplinary, racial, and academic identity [44]. As such, it is important to consider how technical interviews, and other professional and cultural experiences, may impact students, and especially minoritized populations [3, 4, 29, 45]. Previously **professional experiences** have been described as the “interactions, situations, and events individuals encounter while serving in a particular workplace role” [24], and also include skill development (e.g., training/leadership opportunities), defining career goals, and/or networking [46]. In this research, we extend the definition to include the hiring process, and specify the development of computing skills (e.g., participating in coding bootcamps or freelance computing-related jobs). Meanwhile, we define **cultural experiences** as the knowledge learned and shared, for which activities, behaviors, and the interpretation of experiences define everyday life [1, 11, 30]. We consider items like day-to-day responsibilities (e.g., caring for others) and social support (in terms of home environment and peers).

Presently, it is unclear how professional and cultural experiences impact students' computing identity. **Computing identity** refers to the way that students perceive themselves with respect to computing fields (i.e., computer science (CS), computer engineering



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(CE), and information technology (IT)). Since students each have their own circumstances and pathways, it is also vital to consider the experiences of students with varying social identities.

Social identity refers to an individual's self-perception in relation to others [15, 32]. It includes race, ethnicity, gender, socioeconomic status, sexual orientation, religion/spirituality, age, etc. [15]. In our work, we focus solely on gender, race, and ethnicity.

This information can provide insight into ways to improve student engagement, resilience, and computing identity development, as well as supports/barriers for students looking to start their career. Such analysis is critical for exploring factors that may attract/repel groups already underrepresented in computing. To address this gap in the literature, we sought to answer the following research questions: **RQ1**) *What are the variations in students' experiences with technical interviews across different groups?*; **RQ2**) *How do technical interviews and other professional experiences impact computing identity?*; **RQ3**) *How do cultural experiences impact computing identity?*

2 RELATED RESEARCH

There is limited research on computing identity [28, 33, 42, 43], particularly in the context of underrepresented groups [15, 37, 38]. However, experiences and cultural goals (e.g., helping others) often play a role in aspects of computing identity such as sense of belonging [27] and interest [14]. Literature has expressed the necessity of considering stereotypes and the impact of socialization on minoritized populations in computing [37, 38]. Inhospitable environments and marginalization can make it challenging for them to establish and maintain their computing identity [15, 37].

To this end, professional experiences have demonstrated an important role in computing students' development. Previously Kapoor and Gardner-McCune investigated professional identification with computing, and students long term career goals, and emphasized the necessity of schools offering activities to improve engagement and performance [23]. They suggested that capstone courses, internships, and experiences such as hackathons can help with student development [23, 31].

While it is unclear how professional experiences with hiring affect student development (and retention in the field), whiteboard interviews have been described as a source of stress [2]. The hiring pipeline in computing has been described as "leaky," and it has been mentioned that current practices may discourage qualified candidates and underrepresented groups [4, 5]. Behroozi et al. previously examined students ability to perform problem-solving of technical interview style questions in public and private settings [5]. They detected that think-aloud procedures, and fear of being watched reduced performance. They also observed that while no women were able to successfully solve their problem in public, all were successful in private. They concluded that candidates responses may therefore not be related to problem-solving abilities but rather that "individual responses to stress and extraneous cognitive load can be driving hiring decisions instead of ability."

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

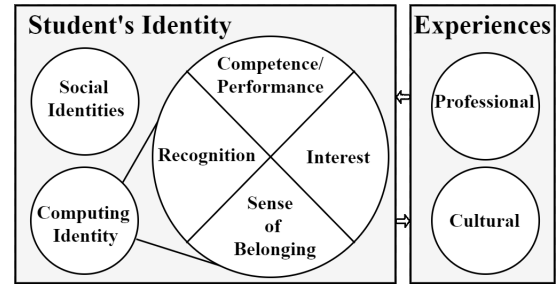


Figure 1: Student identity and experiences

3 THEORETICAL FRAMEWORK

Identity theory considers the multi-dimensional and dynamic conceptualization of self, and the factors that contribute to its development [23, 32]. While many factors may influence a student's identity, in this work we focus on aspects of social identity and disciplinary identity. Disciplinary identity theory has been previously used to understand and evaluate persistence, and career choice in STEM fields [8, 9, 17, 20, 36]. We focus on a specific type of disciplinary identity, computing identity, shown in Figure 1.

Computing identity is conceptualized using the dimensions of competence/performance, recognition, interest, and sense of belonging [42]. **Interest** is defined as a student's cognitive and affective engagement with respect to the subject matter (computing) [28, 43]. **Sense of belonging** is defined as a student's feelings of support and their connection to the computing community [42]. **Recognition** refers to a student's feelings of value and acknowledgement from others such as mentors, teachers, family, and friends [28, 43]. **Competence/performance** is defined as a student's self-confidence in understanding computing and feeling accomplished in that topic. While the components are separate, they often interact and overlap based on context and population [28].

Scholars have argued social identity is a valid basis for understanding student reflection and their interpretation of engagement in computing fields [32]. Also, computing professional identity has been examined in terms of how students develop as professionals within their major and in the field. Previously, Kapoor and Gardner-McCune (2019) used James Marcia's Identity Status Theory to describe how social, personal, and cultural identity can influence professional identity development in computing [23]. They found that typically CS undergraduates form their computing professional identity between year 2 and 3 of their degrees, and that prior to this time, students may explore computing professions without being committed. It is suggested this relates to a lack of experience, doubts about technical competency, and/or indecisiveness. They stress the importance of educational environments that help to students obtain technical skills and knowledge, while supporting engagement in the community to build computing professional identity. As such, we seek to examine the impact of TIs, and other professional and cultural experiences on computing identity, for students from different backgrounds.

4 METHODS

4.1 Survey Development and Administration

To analyze students' technical interview, professional, and cultural experiences, and their impact on computing identity, we leveraged

Table 1: Computing identity construct factor loadings

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

***p < .001

a survey instrument. We used questions previously validated on STEM identity [9, 20, 42], to ensure our construct included reliable and accurate measures. Apart from inquiring about demographic information, items included asking about students' academic standing (year in school, major, and GPA), and inquiries into the students' educational history, home life, persistence, interests, and experiences. Questions were also added about the hiring process in computing, resulting in a total of 46 questions.

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

4.2 Demographics

Our sample was an $n = 740$, of which 23.0% were female, 74.9% were male, and 2.1% reported as either transgender, agender, or a gender not listed. Racial/ethnic group affiliation of the students were: 42.2% White, 8.4% Black or African American, 14.9% Asian, 1.1% Native Hawaiian or Pacific Islander, 0.4% American Indian or Alaskan Native, 32.7% were Hispanic, Latinx, or Spanish origin, 2.4% Middle Eastern or North African, and 1.6% another race or ethnicity not listed. For year in college, 6.8% of students were in their 1st year, 9.5% were in their 2nd year, 18.5% were in their 3rd year, 43.4% were in their 4th year, and 21.8% were past the 4th year.

4.3 Analytics

We used R (version 3.6.1) to clean and analyze the data. Statistical analyses consisted of descriptive statistics, Wilcoxon rank-sum tests, confirmatory factor analysis (CFA), and regression analysis. For descriptive statistics and the interaction analysis, we focused on the underrepresented minorities of women, Hispanic/Latinx, and Black/African American students. Although the questions pertaining to computing identity were the same as the work previously

conducted [42], since this survey was administered in another year, with a different population, we performed CFA.

CFA was run to confirm that particular questions mapped onto the theorized computing identity sub-constructs [6]. The resulting latent variables for the sub-constructs were defined by the questions (indicator variables) denoted in Table 1. These items were averaged to create proxies for each sub-construct, and these were combined to represent an overall proxy measure for computing identity. All of the standardized factor loadings are above the accepted 0.6 threshold [7]. Although our χ^2 was significant ($p < 0.001$), since our sample was so large, we considered other fit indices to evaluate our model as well (presented below) [6].

The Root Mean Square Error of Approximation was 0.079, which is less than 0.08, and implies an “acceptable fit” [39]. The Comparative Fit Index was 0.952, which is above the threshold for a good model fit (≥ 0.95), and indicates that 95.2% of the co-variation in the data can be reproduced by our model [16]. Likewise, the Relative Fit Index (0.924), Normed Fit Index (0.942), and Non-Normed Fit Index (0.937), were all above the “good fit” threshold as well. Contrarily, for the Standardized Root Mean Square Residual (SRMR), the smaller the value, the better the fit, and a value of 0 suggests a “perfect fit.” In our analysis, the model's SRMR was 0.043, which is less than the 0.05 threshold required to denote a “good fit.”

Regression is a statistical method used to establish relationships between a dependent variable and one (or more) independent variable(s), and to explore their interactions [19]. Specifically we examined how TIs, cultural, and professional experiences predict computing identity. The precise professional experience questions (PEQ) and cultural experience questions (CEQ), and their responses, analyzed in the regression model are shown in Table 2. The final regression model was built using backwards block elimination [19].

5 RESULTS

5.1 Technical Interview Experiences (RQ1)

To answer RQ1 about the variations in students' experiences with technical interviews across different groups, we first examined how many TIs different groups had (PEQ2), and the number of job offers

Table 2: Experiential items assessed

<i>Professional Experiences</i>	
Professional Experience Questions (PEQ)	Responses
PEQ1: Which of the following professional experiences, if any, have you had at your institution with respect to computing? Mark all that apply.	Industry Internship; Research experience; Shadowing experience; Part time or full time job in computing; Mock interviews; Personal computing projects, outside of normal classwork; Freelance computing-related jobs; Hackathons/Programming competitions; Certifications (e.g. CompTIA A+, IT Infrastructure Library (ITIL), Tableau, Project Management, Google Cloud); Coding bootcamps; Networking with industry and other professionals; Attending symposia, conferences, or other computing events; ePortfolio, digital portfolio, or personal website
PEQ2: How many programming or technical job interviews have you completed in computing?	0; 1-2; 3-4; 5-6; 7-8; 9 or more
PEQ3: Which of the following apply to your positive experience(s) with technical interviews. Mark all that apply.	I have NOT had positive experiences; really prepared; the questions asked were relevant for the position; the questions asked were easy; the interviewer treated me like an equal; the interviewer guided me (with hints/help); the interviewer was kind and/or respectful; Other
PEQ4: Which of the following apply to your negative experience(s) with technical interviews. Mark all that apply.	I have NOT had negative experiences; like I was not prepared; the questions were not relevant for the position; the questions asked were too difficult; the interviewer treated me like I was inferior; the interviewer did not provide any guidance; the interviewer was harsh and/or critical; discriminated against; Other
PEQ5: How many job offers have you received in computing?	0; 1; 2; 3; 4; 5 or more
PEQ6: How many hours do you work on computing related jobs outside the home each week?	0; 1-5; 6-10; 11-15; 16-20; More than 20
<i>Cultural Experiences</i>	
Cultural Experience Questions (CEQ)	Responses
CEQ1: How supportive is your home environment towards computing?	5-point Likert scale: Not at all supportive to Extremely supportive
CEQ2: How many friends do you have in computing programs?	0; 1-2; 3-4; 5-6; 7-8; 9-10; More than 10
CEQ3: Which of the following apply to your day-to-day life? Mark all that apply.	Caring for a child (e.g. sibling, your own child); Caring for an adult (e.g. grandparent); Personal recurring health problem (not including common illnesses like a cold or flu); Other

received (PEQ5), as shown in Table 3. The number of job offers was only calculated for students that reported having at least one technical interview ($n = 350$). Percentages were calculated as the representation relative to others within the group.

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

average. We also used regression to verify that the number of TIs was predictive of the number of job offers received ($p < .001$).

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

5.2 Impact of Experiences on Computing Identity (RQ2 and RQ3)

We used regression to examine the impact of technical interviews and other professional experiences on computing identity (RQ2), as well as evaluating cultural experiences on computing identity (RQ3). As shown in Table 4, we first controlled for demographics and background variables not directly associated with undergraduate computing experiences to minimize the effect of confounding variables, and then to estimate the effects of our factors of undergraduate computing experiences more “purely” [19]. 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

Table 3: Technical interviews and job offers, as percentages of total students in sample, means, and standard deviations

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

Table 4: Regression model predicting computing identity measure with interactions

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

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

although we present the control variables, experiential variables, and the interactions as distinct sections in Block II, the model itself was analyzed together. The cultural and professional experiential variables with a significant effect on computing identity pertain to the entire population, whereas the interactions focus solely on marginalized populations (females, Black/African American, and Hispanic/Latinx students). We observed that the adjusted R^2 for our control block was 10.25%, and with the addition of experiential variables, rose to 24.24%. This denotes a 13.99% gain in the variance explained from the experiential variables that were added.

Correlated predictors can cause an issue known as multicollinearity [25]. To determine if this was an issue, we ran variance inflation factor statistics on our models. Typically the threshold is greater than 3.3 [10]. However, for all the variables, all the statistics were less than 1.5, suggesting that multicollinearity is not a substantial issue in our model.

6 DISCUSSION

The majority of computing students reported having TIs (52.00%). Overall, it is encouraging that only 9.43% reported not having any positive experiences. However, the negative experiences encountered demonstrate that there is still room for improvement from students, educators and institutions, and industry. The top negative experience reported was that students felt unprepared. While to some extent students are responsible for remedying this, universities could help to make students aware of what to expect early

in their education, suggesting resources (e.g., LeetCode) and offering increased opportunities to prepare (e.g., mock interviews). They could also offer more examples in courses to expand students' familiarity with different problems, and the application of theory.

In terms of the regression, several of the relationships between professional experiences and computing identity were unsurprising. Students that felt really prepared for TIs had a higher computing identity ($\beta = .15$), and those students that did not have positive experiences with TIs had a lower computing identity ($\beta = -.10$). Also, hours spent working in a computing job ($\beta = .10$), or completing personal computing projects outside of classwork ($\beta = .07$) also positively predicted computing identity. While freelance computing jobs improved computing identity for all students ($\beta = .09$), there was a notable positive interaction for Black/African American students ($\beta = .08$). We posit encouraging computing students to seek out such opportunities or facilitating such latitude may provide students an additional space to showcase their skills, which may contribute to aspects of computing identity like performance and confidence. This aligns with literature that professional experiences can help with student development and performance [23]. However, since freelance jobs allow students to be selective, they may also choose to only take on projects that appeal to them, which may impact their interest as well. Offering students opportunities to take on freelance projects may be a great way to encourage participation in the field, without the rigor and stress associated with TIs. If universities are not presently including such options through

their career services, seeking out partnerships with industry, and developing these opportunities for students could be a great way to add value and encourage development of computing identity.

What was notable in the regression model is that being discriminated against during TIs actually had a positive impact on computing identity ($\beta = .09$). Also, all of the students reporting this experience did belong to groups considered underrepresented in computing. Typically discrimination and bias experiences are considered negative for students, and often result in a diminished sense of belonging and retention for students of color [21, 22]. As such, we further explored which aspects of computing identity were impacted by being discriminated against during TIs. In the new model, we made being discriminated against a predictor for combined measure of computing identity and it yielded an estimate 0.87 ($\beta = 0.10$). Comparatively, the estimate for being discriminated against in predicting sense of belonging alone was 1.24 ($\beta = .10$). In terms of the other sub-constructs — the estimate for recognition was 0.79 ($\beta = .07$), it was 0.90 ($\beta = .08$) for competence and performance, and interest was not significant. This confirmed that being discriminated against during a professional experience had the biggest impact on sense of belonging, extending prior literature about sense of belonging to an institution [22]. Accordingly, we hypothesize these discriminatory experiences may have actually encouraged students to persevere in computing, and rather than deterring them, it pushed them to work harder to succeed [12].

Positive social experiences with supportive individuals play an important role in persistence and development of self-efficacy for minoritized students in STEM fields [18]. In addition, ethnically diverse friends and classrooms can provide additional support to bolster resistance in the face of discrimination [18, 22]. While there were no significant gender or racial/ethnic interactions for discrimination during TIs, we did observe a significant interaction for Hispanic/Latinx students and the number of friends in computing ($\beta = .16$), which led to an improved computing identity. Furthermore, there was a significant interaction effect for females and a supportive home environment ($\beta = .34$). Given that on average females received more job offers than males, the impact of cultural experiences in providing positive support should be considered.

While we have focused on the significant experiences described, we would also like to draw attention to some of those that were not, from the full list examined in Table 2. The absence of certain experiences makes a compelling case that these items could be reworked or redesigned to maximize their benefit to computing students. For example, while the hours spent working in a computing job did predict computing identity, shadowing experience did not. Therefore, it may be less important to observe others, and more meaningful to perform computing in a professional capacity. This aligns with prior work in STEM which demonstrated students prefer learning via hands-on material to abstract material (i.e., concepts, theories) [26]. Students in computing have also been shown to have a more positive self-image when applying exploratory problem solving, and finding their own solutions to problems [41]. Thus, the way shadowing opportunities are presently structured may need refinement. Future research could investigate more effective ways of setting up such experiences. Additionally, although qualitative research has suggested informal activities like hackathons/programming competitions may help computing students to meet others, and

may be influential in career choices [23], they did not predict computing identity. As such, their impact on computing identity may be less overt and instead mediated through aspects such as serving to reinforce skill development.

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

7 LIMITATIONS

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

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

8 CONCLUSIONS

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

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