Work In Progress: A Novel Approach to Understanding Perceptions of Race among Computing Undergraduates

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I am currently a Postdoctoral Research Associate with the Alliance for Identity-Inclusive Computing Education (AiiCE) at Duke University. My research interests include the areas of racial inequality, social networks, higher education, and knowledge creation. Currently, my research focuses on how racialized networks in computer science disproportionately advantage whites and leads to racialized knowledge production and legitimization. I received a B.S. in Mathematics from Longwood University in 2012, an M.S. in Sociology with graduate minors in Mathematics and Statistics from Iowa State University in 2015, and a Ph.D. in Sociology from Duke University in 2022.

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INTRODUCTION

Black, Native American, Native Hawaiian/Pacific Islander, and Latinx undergraduates remain severely underrepresented in computing [i.e., computer science (CS), engineering, and information systems] [1]. This is often attributed to student-centered, deficit-based factors such as a lack of access to K-12 computing courses, culturally relevant role models and curricula, and sense of belonging. However, research notes how racial "othering" in university courses, departments, and cultures from peers, faculty, and staff negatively impact them [2]–[4].

Shifting national conversations around race, racism, and anti-racism [5] have led departments to rethink strategies for increasing degree entry, retention, and completion among people from ethnoracial groups that are historically underrepresented in computing [6], [7]. For example, STEM departments across the globe participated in #ShutDownSTEM in support of the Movement for Black Lives [8], [9]. However, to the best of our knowledge, how computing undergraduates make sense of race and racial (under)representation (if at all) has not been studied.

RELEVANT LITERATURE

K-20 STEM Student Perceptions of Race

The relationship between racialized academic experiences, sense of belonging, and academic success and degree completion of Black, Native American, Native Hawaiian/Pacific Islander, and Latinx students has been noted throughout literature on K-20 STEM education. Racial microaggressions that occur in classrooms and academic relationships between students and peers, educators, and staff significantly impact even the most successful students, regardless of institution type [10]–[13]. In some instances, these experiences negatively impact sense of belonging in not only students from racial groups that are historically underrepresented, but also those from non-white groups that are overrepresented in computing (i.e., Asian) [14].

The study in [15] examined how STEM majors from various racial groups perceive differences in their STEM experiences based on racial identity. Fourth-year students from the University of North Carolina (UNC) system (comprising all public universities in North Carolina) were interviewed about their experiences in STEM. It was determined that most students identifying as white men were unaware of the impacts of race or gender in the field. Conversely, "women of color overwhelmingly report, consistent with results from a large body of prior research, that both race and gender impact their experiences as STEM majors" [15].

Similarly, a study of high-school student perceptions of race and gender reported that participants attributed racial underrepresentation in STEM to historical and contemporary systemic inequalities, racial stereotypes ascribed upon entering STEM fields, and personal experiences of discrimination and microaggressions [16]. While participants stated that racial and gender underrepresentation in STEM is problematic, some still rearticulated stereotypical narratives.

K-20 STEM Educator Perceptions of Race

An investigation of the dialogues around race and computing within K-12 CS teacher professional development workshops found that white teachers tend to avoid conversations, practices, and activities that explicitly acknowledged race, while teachers of color directly named topics related to race [17]. Another study of how teachers perceive and discuss racial and gender stereotypes in their classrooms reported that the majority of the respondents noted they did not have the time nor the training to have conversations about diversity, stereotypes, and racism in their classrooms [18].

At the postsecondary level, a study of STEM faculty found that "while many faculty members implicated systemic racism in their sense making about the underrepresentation of racially minoritized students in STEM, the majority used colorblind frames […] by focusing on individual behaviors and choices, cultural deficits, under-preparation, and poverty" [19]. As such, "[p]rofessors were able to explain racial phenomena without implicating race/racism, which allowed them to absolve themselves from responsibility in addressing racial inequality issues in higher education" [19]. Similarly, the work of [20] uncovered how race-neutral rhetorical strategies used by faculty continue to normalize whiteness as the default in STEM, while simultaneously minimizing the systemic inequalities faced by racially marginalized people. As with [19], this work highlights the contradictions inherent in such rhetorical strategies among STEM faculty:

The incoherence of [the participant's] answer – in expressing a hesitancy to accept race as a determining factor in success, citing a need for a controlled experiment, while also asserting with certainty that it is his mother that has conferred advantage to him (without doing a controlled experiment) – is consistent with race-evasiveness but not with the expectation of coherence in scientific explanations.

Limitations of Existing Studies

The studies on postsecondary student perceptions of race in STEM are limited by several factors. First, geographical location was restricted to students in the UNC system, which comprises 16 universities [historically white colleges and universities (HWCUs) and historically Black colleges and universities (HBCUs)]. This study does not account for different institutions (and types) across the United States, which may impact how students understand, perceive, and experience race. Additionally, North Carolina does not have any Tribal Colleges and Universities (TCUs).

Second, the study targeted fourth-year undergraduate STEM majors, with no inclusion of other classifications. The inclusion of students earlier in their college studies would potentially capture more non-university-related influences on student perceptions. Third, the study included only a qualitative instrument, thereby limiting the number of participants. Fourth, the study was not restricted to computing students. While non-computing STEM majors suffer from the same lack of representation, it is important for researchers in computing to understand discipline-specific perceptions and experiences. Finally, the study did not account for other student identities outside of race and gender. This excludes more nuanced analysis of results, based on multiple forms of oppression that students may (not) experience [21]. In addition, the computing community lacks significant data collection efforts related to students with disabilities, highlighting the need to account for this important (and often overlooked) identity [22].

This work-in-progress paper is situated within a broader ongoing project that seeks to answer two research questions. First, how do computing undergraduates perceive race? Second, what factors influence these students' understanding of and experiences with race in the context of university computing departments?

This paper seeks to fill an important gap in the literature on how computing undergraduates understand, perceive, and experience race. Specifically, it presents the development and pre-testing of two instruments that comprise a mixed-methods approach for understanding student perceptions of race and the factors influencing them. The instruments are inspired by and expand upon the Detroit Area Study [23] and a study of physics faculty perceptions of race by Robertson et al. [20].

Prior research has shown that even when individuals can describe inequalities as structural, their sense-making about differential outcomes tends to remain centered on individual explanations. By leveraging a mixed-methods approach, this study captures whether computing undergraduates identify racial inequality as structural and believe racial inequality is the result of individual actions or circumstances.

The instruments consist of a quantitative survey and a qualitative protocol for one-on-one, semi-structured interviews. Items within both instruments were originally organized into constructs based on home environment; college environment; belonging/comfort in computing courses and departments; perceptions of race; diversity, equity, and inclusion (DEI) policies and practices; and definitions of race. The instruments were distributed during the fall 2022 and early spring 2023 semesters. The results from both instruments, including open-ended feedback, were used for final revisions.

METHODS

Both the quantitative and qualitative instruments were developed iteratively during the fall 2022 semester. Prior to instrument development, the Detroit Area Study and Robertson et al. protocols were reviewed to identify relevant items to adapt.

Quantitative Instrument Development

The original quantitative instrument consisted of 45 items, seven of which collected demographic information. The remaining 38 items were organized into five constructs: home environment; college environment; belonging/comfort in computing courses and departments; perceptions of race; and DEI policies and practices. Items related to views on systemic oppression, affirmative action, assumed (disadvantages) in hiring, and social networks were adapted from the Detroit Area Study and Robertson et al. All items were reviewed, revised, and/or removed in an iterative process for clarity, repetition, and conciseness.

The second version of the instrument was reduced to 35 required items: seven demographic and 28 closed-ended. Special attention was paid to language and framing that would be most appropriate for the population of interest. All closed-ended items included scale responses related to frequency (Most, Some, Few, None) or Likert-scales related to level of agreement (Strongly Disagree, Disagree, Neither Disagree Nor Agree, Agree, Strongly Agree, Not Applicable). Two additional items allowed participants to select items that were confusing/unclear and provide open-ended feedback.

The 35-item instrument was distributed for pre-testing, and items were revised/removed based on responses. Following revisions, the third (and final) instrument contained a total of 36 items. Table 1 includes the final set of items, with their original construct mappings.

Table 1. Final quantitative instrument items.

<table>
<tr>
<td>Demographic Info
1. In what state (or country, if born outside the U.S.) were you born?
2. In what state (or country, if outside the U.S.) did you spend most of your formative years (i.e., ages 6-18)?
3. What is your racial identity?
4. What is your gender identity?
5. Do you have a disability or other chronic condition?
6. Are you part of the first generation in your family to attend college?
7. Did you take formal computing courses in high school?</td>
<td>Construct 1: Home Environment
1. Growing up, how many people in your neighborhood had the same racial identity as you?
2. How many students in your high school had the same racial identity as you?
3. Before college, how often did you discuss race and/or racial discrimination with:
o Immediate family (i.e., those living with you)
o Three closest friends
o People in gathering places (e.g., park, community center, place of worship)
o Classmates
o Teachers?</td>
</tr>
<tr>
<td colspan="2">Construct 2: College Environment
1. University Name
2. In what country is your university located?
3. In what state/territory is your university located?
4. What type of university do you attend? Note: This is not your racial identity. If you are unsure, select "Not sure."
5. Select which is the closest to your major:
6. Classification
7. How many students in your <u>computing courses</u> have the same racial identity as you?
8. How many students in your <u>non-computing courses</u> have the same racial identity as you?
9. Are you a member of any department-related computing organizations (e.g., Association of Computing Machinery)?
10. Are you a member of any university clubs or organizations?
11. In your computing department, do you have opportunities to learn about topics related to race in:
a. Courses
b. Workshops/lecture series</td>
</tr>
<tr>
<td colspan="2">Construct 3: Belonging/Comfort in Computing Courses/Departments
1. *I frequently discuss topics related to race and/or racial discrimination with:
a. My three closest college friends
b. Classmates (major courses)
c. Classmates (non-major courses)
d. Other students in department-related computing organizations you participate in (if any)
e. Other students in university clubs/organizations you participate in (if any)?
2. *I would be comfortable being one of the few people or the only person in a computing class who has my racial identity.</td>
</tr>
</table>

3. *I am comfortable discussing topics related to race and racial discrimination with computing department faculty and/or staff who: a. *Have the same racial identity as me b. *Do not have the same racial identity as me 4. *I feel like people assume my performance in class reflects my racial group. 5. *I feel like I must suppress aspects of myself to be successful in my computing department.
Construct 4: Perceptions of Race 1. *I consider myself very knowledgeable about topics related to race. 2. *Black, Native/Indigenous, and Latinx people are underrepresented in computing majors. Depending on who you ask, some people think it is because of one or more of the reasons listed below. How much do you agree/disagree with these statements as potential reasons? a. *They were not exposed to computing early as a K-12 student. b. *They experienced isolation and/or exclusion in K-16 computing courses. c. *They do not work as hard to be successful in computing courses. d. *They experienced bias or discrimination from faculty, staff, and students in computing courses and departments. e. *They are not interested in computing. f. *They must suppress aspects of themselves to be successful in computing environments. g. *They have faced a lack of opportunities in the U.S. due to systemic issues of oppression. h. *They are not as strong in math or computing. i. *They did not have the financial resources to pursue computing courses. 3. *How much do you agree with the following statements? a. *Race has no impact on the work I plan to do professionally. b. *The technologies that we often use are neutral and racially unbiased. c. *University computing departments are neutral and racially unbiased. d. *Professional computing environments are neutral and racially unbiased. e. *My race advantages me in the field of computing in terms of internships and job opportunities. 4. *Please note how much advantage (in terms of internships and job opportunities) do you think there is for being the following in computing: a. *A woman b. *A man c. *A non-binary person d. *A White person e. *An Asian person f. *A Black person g. *A Native or Indigenous person h. *A Latinx person i. *A person with a disability j. *A person without a disability
Construct 5: DEI Policies and Practices in Computing 1. *The Supreme Court is considering if college admissions policies that consider race should be allowed. Some people support these policies, while others are against them. Do you support or oppose considering race in the college admissions process? 2. *Many university computing departments and companies have programs designed for Black, Native, and Latinx students and graduates (e.g., mentoring, pre-college programs, and affinity groups). Some people think these create more diversity. Do you agree? 3. *Many universities created institutional anti-racism programs and commitments over the last few for all students to learn more about race. Do you think these commitments and programs are important for students of all races?

4. *Many university computing departments think it is important for students to learn more about topics related to race prior to graduation. Do you agree?
Construct 6: Definition of Race 1. Do you think there are biological differences between different races? 2. If you had to give a definition of the word "race" or explain what it was, what would you say?

Qualitative Instrument Development

The qualitative instrument further explored responses to the quantitative instrument. The initial version included 25 items. All items were organized under the following six constructs: interest in computing, home environment, college environment, belonging/comfort in computing courses and departments, perceptions of race, and diversity-related computing policies and practices. Items were reviewed for redundancy, lack of clarity, and flow.

Some questions that were relevant to the research but not suited for a survey were adapted into the qualitative instrument. As a result, several questions were open-ended versions of items initially drafted during development of the quantitative instrument. This allowed the analysis of the quantitative and qualitative results to be mutually constitutive.

Following a review/revision of all items and pre-testing, the qualitative instrument was reviewed for redundancy, lack of clarity, and flow. Some items were removed, and others were added, for a final total of 26 potential items (Table 2). The primary reason for the large number of items was to provide interviewers with as much clarity as possible on what the research aimed to elicit from respondents and autonomy to follow an appropriate flow for any respondent. Interviewers were instructed to not formulaically recite every question, but rather ensure that the thematic and topical elements in each question and construct were covered throughout the interview. While the qualitative instrument does have several closed-ended questions, interviewers were trained to follow up and elicit further information for these items.

Table 2. Final qualitative items.

Introduction 1. When did you become interested in computing? 2. What are some qualities, characteristics, or personality traits that you think are necessary to be a good computer scientist? 3. Are you happy about choosing computing as a major? Why or why not?
Construct 1: Home Environment 1. When did you start thinking about/noticing race? Was there a particular incident that made it apparent? 2. Who were your closest friends? 2. What did you do together? How frequently? 3. What are their races?
Construct 2: College Environment 1. What do you do in your free time outside of class? What kinds of things do you do together? 2. What are your interactions with faculty in the department like? 3. Now thinking about other *students* in your computing classes, what are your interactions with them like inside of class? What about outside of class? 4. Do you think COVID has impacted your college experience? How so?

5. Have you ever had any conversations related to race on campus? With whom?
Construct 3: Belonging/Comfort in CS Courses/Departments 1. Do you feel comfortable expressing your thoughts and opinions related to race and racial discrimination with people in your department who share your racial identity? Why or why not? What about those who don't? 2. Do you feel like you behave the same way in your computing department as you behave with your friends and family?
Construct 4: Perceptions of Race 1. How much do you think race will impact the work you plan to do professionally? 2. Do you think the technology that is developed is neutral and racially unbiased? 3. Do you think academic computing departments are neutral and racially unbiased? 4. Do you think professional computing departments are neutral and racially unbiased? 5. Do you think your race advantages you in the field of computing in terms of internships, jobs, and other opportunities? How so? 6. Research indicates Black, Native/Indigenous, and Latinx people are underrepresented in computing majors and careers. Why do you think that is? Has that been your observation in your department / classes? 7. Do you think race impacts the experiences of all students in university computing departments? 8. Do you think race impacts the experiences of all professionals in industry computing careers?
Construct 5: DEI Policies and Practices in CS 1. Some people think that because of past discrimination against Black, Native/Indigenous, and Latinx people, preference in college admissions, hiring, and promotions should be given if all other factors (e.g., education, standardized test scores, and work experience) are equal. Others think preferential admissions, hiring, and promotion give Black, Native/Indigenous, and Latinx people advantages that they haven't earned. What do you think? 2. Many university computing departments and companies have programs to recruit/retain Black, Native, and/or Latinx students/graduates (e.g., mentoring, pre-college programs, and affinity groups). Some people think these create more diversity. Others think they create more division by highlighting race. What do you think? 3. Has your university made any institutional commitments to anti-racism or learning about race and racism? 4. Have there been any steps taken in your department to teach computing majors about topics related to race and racism?

Data Collection Process

The target population was undergraduate computing students ages 18 years or older. Data collection occurred during the fall 2022 and early spring 2023 semesters. Participants for both instruments were solicited via recruitment emails to faculty at various institutions via listservs that specifically targeted computing educators and organizations serving groups that are historically underrepresented in STEM, including the Association for Computing Machinery (ACM), Black in Computing, the Academic and Research Leadership (ARL) network (Black in Electrical Engineering), the ACM Special Interest Group in CS Education (SIGCSE), and the National Science Foundation's Inclusion across the Nation for Communities of Learners and Underrepresented Discoverers in Engineering and Science (INCLUDES) Network. Participants received an introductory email detailing the purpose, informed consent form, and survey link.

In the fall 2022 pre-tests, approximately 95 participants completed the quantitative survey, and seven participants completed the qualitative interview protocol. Responses and feedback on these instruments resulted in the finalized instruments in Tables 1 and 2. In the spring 2023 pre-tests, a total of 353 respondents from 26 colleges and universities completed the survey. Ten incomplete responses were removed. An additional 17 non-undergraduate (i.e., graduate student) responses were removed, leaving a final sample of 326 respondents who fully completed the survey. All data was collected via Qualtrics and exported into a CSV file for analysis.

Data Analysis and Validation

Quantitative Instrument

Analysis of the quantitative instrument was conducted on the items (and corresponding sub-items) in Constructs 3-5 (marked by '*') in Table 1. The items corresponding to Construct (denoted hereafter by *C*) C3.1.a-e ("I frequently discuss race with…") were condensed into one aggregate variable that represented the mean of all valid responses for each item. This aggregation accounted for "Not Applicable" responses and retained the underlying concept of how often one discusses race. Items corresponding to C4.2.a, b, d, f, g, and i; as well as C5.1 and C5.4 were rescaled for consistency in numerical interpretation. For example, C5.1 and C5.4 were rescaled so that all items related to DEI policies and practices represented lower values as support of DEI policies and practices and higher values as opposition.

Analysis of the Quantitative Instrument

Responses to the quantitative instrument were used to determine the survey's internal reliability, factorability, and underlying constructs [24]. Internal reliability was assessed using Cronbach's α, which measures the extent to which items measure the same concept [25]. The minimum acceptable value for Cronbach's α is 0.6-0.7 [26]. Since this survey is exploratory and addresses several interrelated and complex concepts, Cronbach's α is not expected to be high or provide evidence for unidimensionality of the instrument. However, reliability was tested to further understanding of the internal consistency of each construct identified in the survey.

Exploratory factor analysis was then completed using Python version 3. Analysis included testing of both orthogonal (varimax method) and oblique (promax method) rotations. The final eight-factor model used promax rotation, an oblique rotation method that allows factors to correlate. Allowing for correlation was meant to help the factors better reflect the relationship among these underlying concepts. After the model was determined, factors were named based on interpretability and prior literature.

Qualitative Instrument

Unlike in quantitative analysis, where specific tests are used to ascertain the validity of an instrument, qualitative analysis requires a continuous process of reflexivity and reinspection by the research team. Whereas in quantitative research, the goal is to accurately and reliably match measures to the constructs they represent, the strength of qualitative research is to give richer understandings and explanations of social phenomena of interest.

The interviewers and interviewees were race-matched following best practices. The pre-test interviews uncovered further details that were addressed in subsequent protocol reviews. For example, the pre-test revealed the COVID pandemic as a continuing influence on student experiences. Appropriate probes were added to account for this and other items of note. A new item on racial identity was added that asked participants to expand on their selections from the quantitative instrument to capture a more nuanced understanding of perceptions of their own race.

RESULTS

Study Sample

The sample demographics from the fall 2022 distribution of the quantitative survey included students from three institutions (one HBCU and two HWCUs). Approximately 48% identified as Black or from the African Diaspora, 3% Latinx/Hispanic, 19% white, 21% Asian, 1% Middle Eastern or Northern African, and 8% two or more races. Approximately 44% identified as men, 46% women, 3% non-binary, and 7% did not disclose. Approximately 13% reported a disability or other chronic condition, 80% did not, and 7% did not disclose. First-year students represented approximately 2% of all respondents, sophomores 9%, juniors 47%, and seniors 42%.

The spring 2023 distribution of the survey were compared with the 2021 Taulbee Survey [27], which is representative of enrollment in undergraduate computing programs. This sample matched the demographics of computing racially, with most respondents identifying as white (37.4%, n = 122) and Asian (35.6%, n = 116). Other races represented were Black or from the African Diaspora (7.7%, n = 25), Latinx/Hispanic (3.7%, n = 12), Native American (1.2%, n = 4), Middle Eastern or Northern African (0.6%, n = 2), two or more races (13.2%, n = 43), and other identities not listed (0.6%, n = 2). While men represent approximately 70% of all computing undergraduates, the gender demographics of the sample had a higher representation of women (45.7%, n = 149) and non-binary/gender non-conforming people (6.7%, n = 22). Most respondents spent their formative years (ages 6-18) in the United States (80.4%, n = 262). Approximately 17.5% (n =57) of all respondents have a disability or other chronic condition, and 82.5% (n=269) did not. Student classifications were fairly evenly distributed across first- (19.6%, n = 64), second- (30.4%, n = 99), third- (30.4%, n = 99), and fourth-year (19.6%, n = 64) students. Approximately 23% (n = 76) of all respondents were first-generation college students. The overwhelming majority of students (94.8%, n = 309) attended HWCUs.

Reliability

Cronbach's α for the full instrument is 0.749, which surpasses the minimum acceptable value [25]. Cronbach's α for the three predetermined constructs (C3: belonging in computing, C4: perceptions of race, and C5: DEI policies and practices (Table 1) was 0.278, 0.782, and 0.601, respectively.

Determining Factorability

To determine if the items in quantitative instrument were eligible for factor analysis, the Kaiser-Meyer-Olkin (KMO) test and Bartett's test for sphericity were conducted. The Kaiser-Meyer-Olkin (KMO) test assesses item-to-item correlation, where a value greater than 0.5 is sufficient for factor analysis [28]. The KMO value for this data was 0.867. Bartlett's test for sphericity produced a p-value of 0.0, which satisfies the condition of a p-value less than 0.05. These two results provide sufficient evidence that the data were eligible for factor analysis [28].

Factor Structure

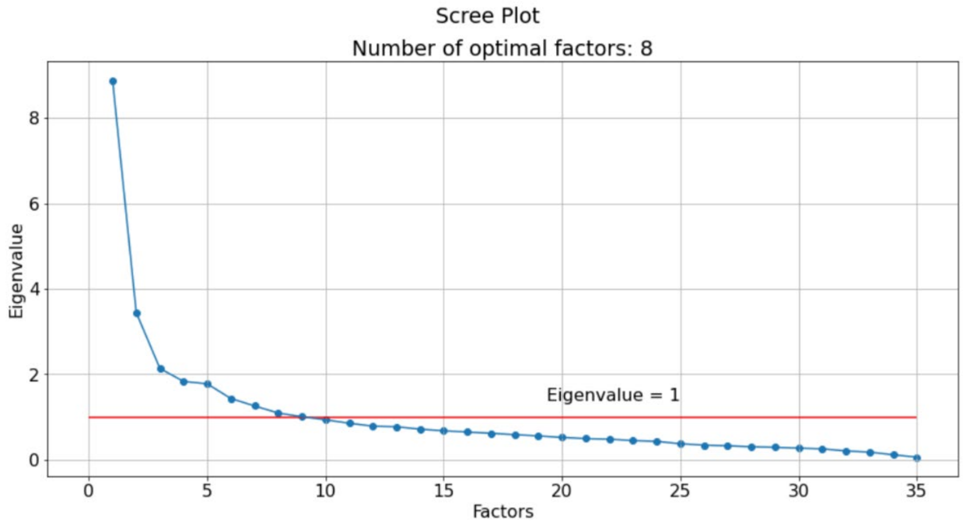

Figure 1. Scree plot.

The number of factors was chosen based on the Kaiser criterion of eigenvalues greater than one [29], observations via scree plot (Figure 1), and interpretability of the factors. The eigenvalues and subsequent scree plot indicated that eight factors were optimal for these data, which accounted for 56.2% of the cumulative variance in the instrument. Following best practice and to compare model fit and interpretability, extractions were also conducted on seven and nine factors using both orthogonal and oblique rotations. Additionally, factor analysis was performed using three factors, based on the three original constructs (belonging/comfort in computing, perceptions of race, and DEI policies and practices). This three-factor model accounted for the lowest cumulative variance of 35.3% and was less interpretable than models with seven, eight, or nine factors. Comparing the results across all four models, the most appropriate model contained eight factors with oblique promax rotation, which retained the most items with significant factor loadings and provided clearly interpretable factors.

Tables 3, 4, and 5 summarize the variances of the three-, seven-, and eight-factor models, respectively.

Table 3. Variance of three factors chosen using promax rotation.

Factors	**1**	**2**	**3**
eigenvalues	4.978479	4.636853	2.737991
variance	0.142242	0.132482	0.078228
cumulative variance	0.142242	0.274724	0.352952

Table 4. Variance of seven factors chosen using promax rotation.

Factor	**1**	**2**	**3**	**4**	**5**	**6**	**7**
eigenvalue	4.281029	3.619811	2.76598	2.760486	2.091548	1.687038	1.367742
variance	0.122315	0.103423	0.079028	0.078871	0.059759	0.048201	0.039078
cumulative variance	0.122315	0.225738	0.304766	0.383637	0.443396	0.491597	0.530675

Table 5. Variance of eight factors chosen using promax rotation.

Factors	**1**	**2**	**3**	**4**	**5**	**6**	**7**	8
eigenvalue	4.321653	3.686285	2.894175	2.786506	2.209111	1.58296	1.391981	0.809398
variance	0.123476	0.105322	0.082691	0.079614	0.063117	0.04522	0.039771	0.023126
cumulative variance	0.123476	0.228798	0.311489	0.391103	0.454221	0.49944	0.539219	0.562345

Table 6 presents the final factor (construct) names, items loading within each, and the corresponding factor loadings.

Table 6. Subitem descriptions and factor loadings of final quantitative instrument.

	Factor Loading
Factor 1: Perceptions of groups that are historically underrepresented in computing (α = 0.931)	
Please note how much advantage (in terms of internships and job opportunities) do you think there is for being the following in computing:	
1. A Latinx person	0.982
2. A Native American person	0.945
3. A Black person	0.924
4. A woman	0.753
5. A non-binary person	0.712
6. A person with a disability	0.647
Factor 2: Race neutrality in computing (α = 0.825)	
How much do you agree with the following statements?	
1. Professional computing environments are neutral and racially unbiased.	1.072
2. Professional computing environments are neutral and racially unbiased.	1.057
3. The technologies that we often use are neutral and racially unbiased.	0.740
4. Race has no impact on the work I plan to do professionally.	0.548
Factor 3: Perceptions of groups that are historically overrepresented in computing (α = 0.831)	
Please note how much advantage (in terms of internships and job opportunities) you think there is for being the following in computing:	
1. A man	0.942
2. A white person	0.833
3. An Asian person	0.752
4. A person without a disability	0.709
Factor 4: Structural perspectives of underrepresentation in computing (α = 0.805)	
Black, Native/Indigenous, and Latinx people are underrepresented in computing majors. Depending on who you ask, some people think it is because of one or more of the reasons listed below. How much do you agree/disagree with these statements as potential reasons:	
1. They have faced a lack of opportunities in the U.S. due to systemic issues of oppression.	0.781
2. They did not have the financial resources to pursue computing courses.	0.738
3. They experienced isolation or exclusion in K-16 computing courses.	0.682
4. They were not exposed to computing early as a K-12 student.	0.653
5. They experienced bias or discrimination from faculty, staff, and students in computing courses and departments.	0.431
6. They must suppress aspects of themselves to be successful in computing environments.	0.307
Many universities created institutional anti-racism programs and commitments over the last few for all students to learn more about race. Do you think these commitments and programs are important for students of all races?	0.330

Factor 5: Individual perspectives of underrepresentation in computing (α = 0.764) Black, Native/Indigenous, and Latinx people are underrepresented in computing majors. Depending on who you ask, some people think it is because of one or more of the reasons listed below. How much do you agree/disagree with these statements as potential reasons? 1. They do not work as hard to be successful in computing courses. 2. They are not as strong in math or computing. 3. They are not interested in computing.	 0.939 0.772 0.627
Factor 6: Comfort discussing race (α = 0.685) I am comfortable discussing topics related to race and racial discrimination with computing department faculty and/or staff who: - Do not have the same racial identity as me. I am comfortable discussing topics related to race and racial discrimination with computing department faculty and/or staff who: - Have the same racial identity as me.	 0.932 0.689
Factor 7: Personal advantage(s)/pressure based on race (α = 0.437) I feel like people assume my performance in class reflects my racial group. How much do you agree with the following statement: “My race advantages me in the field of computing in terms of internships and job opportunities.” I feel like I must suppress aspects of myself to be successful in my computing department. ~~I would be comfortable being one of the few people or the only person in a computing class who has my racial identity.~~	 0.584 0.542 0.432 ~~-0.384~~
Factor 8: Knowledge about topics of race (α = 0.483) I consider myself very knowledgeable about race. I frequently discuss topics related to race and/or racial discrimination	 0.727 0.386

Three items (C5.1, 2, and 4 of Table 1) did not map to any of the eight factors using the lower-bound significance level of 0.3 loading. All three items were in the original construct “DEI Policies and Practices.”

Cronbach's α for each factor highlights varying degrees of internal consistency. Factor 7’s Cronbach’s α was initially 0.071 when including all items that loaded onto it. Removing the item that negatively loaded (indicated by strikethrough) resulted in a new α of 0.427. Factors 7 and 8 have slightly lower values than what is commonly accepted.

Factor Correlations

Factors 1, 3, and **7** were the most highly correlated. **Factors 1** and **3** (r = -0.598) have a moderate negative correlation. **Factors 1** and **7** (r = 0.717) have the highest correlation between any of the eight factors. Finally, there was a negative relationship between **Factors 3** and **7** (r = -0.536). Other, weaker correlations existed between **Factors 1** and **5** (r = 0.490), **Factors 5** and **7** (r = 0.484), and **Factors 6** and **7** (r = 0.483). Table 7 contains a full breakdown of the correlations.

Table 7. Correlation matrix for main factors in EFA.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**

1	1							
2	0.415	1						
3	-0.598	-0.247	1					
4	0.347	0.093	-0.300	1				
5	0.490	0.460	-0.369	0.322	1			
6	0.342	0.100	-0.291	0.173	0.038	1		
7	0.717	0.429	-0.536	0.307	0.484	0.483	1	
8	-0.183	-0.240	-0.056	0.134	-0.235	0.055	-0.171	1

Discussion

Factor Labeling

The eight-factor model was the most interpretable based on previous literature related to racial attitudes in STEM. Items with the highest coefficients also influenced the factor labels. This eight-factor model resulted in the deconstruction of Construct 3 (*belonging/comfort in CS courses and departments*) into two subcategories and Construct 4 (*perceptions of race*) into six subcategories.

Factor 1 (*perceptions of groups that are historically underrepresented in computing*) represents the perceptions of (dis)advantage in computing for Latinx, Native American, Native Hawaiian/Pacific Islander, and Black people; women; non-binary people; and people with disabilities. **Factor 3 (***perceptions of groups that are historically overrepresented in computing*) describes perceptions of (dis)advantage in computing for men, white and Asian people, and people without disabilities. These two factors align with prior literature on stereotypes and the underrepresentation of students in STEM [14] [30].

Items in **Factor 2** (*race neutrality in computing*) assess respondents' beliefs of race neutrality within computing environments and technology. There is growing interest in the biases in both technology and tech environments. As Robertson et al. note that a critical assessment of racism is at times avoided by the assertion of objectivity and neutrality in other STEM disciplines [20], this factor highlights how computing undergraduates think about this topic.

Factor 4 (*structural perspectives of underrepresentation in computing*) describes structural barriers to representation in computing for students who identify as Black, Native American, Native Hawaiian/Pacific Islander, and Latinx. In contrast, **Factor 5** (*individual perspectives of underrepresentation in computing*) describes individual perspectives on underrepresentation. This expands on prior studies that that discuss individual and structural barriers to broadening participation in computing.

Factor 7 (*personal advantage(s)/pressure based on race*) describes respondent reflections on how their race impacts their experience in computing. This factor aligns with past literature on sense of belonging and comfort in STEM fields, especially for groups that are historically underrepresented [31].

Factor 6 (*comfort discussing race*) describes respondents' comfort levels discussing race with people of the same and different races, while **Factor 8** (*knowledge about topics of race*) describes self-assessed knowledge about topics of race and the frequency of discussions related to race and racial discrimination. These factors address ability and comfort with respect to discussing race, which supports literature on the importance of acknowledging race and racial bias to see and address racial disparities in education [32].

In none of the models using 9, 8, or 7 factors were Factors 1 and 3 (*underrepresented* vs. *overrepresented*) or Factors 4 and 5 (*structural* vs. *individual perspectives*) perfect inverses of each other. This reveals that these categories of thought are not necessarily binary. Additionally, the items corresponding to DEI policies and practices were not significantly loaded on any of the factors in most models tested. The highest factor loadings for these items were typically associated with Factor 4 (*structural perspectives of underrepresentation in computing*). For example, "*Many universities created institutional anti-racism programs and commitments over the last few for all students to learn more about race. Do you think these commitments and programs are important for students of all races*?" loaded onto Factor 4 with a loading of 0.33.

Despite the low factor loading of items C5.1, 2, and 4 (Table 1), they were kept in the survey instrument, as they provide insight into participant beliefs about practices to address underrepresentation in computing. That they do not correlate with participant beliefs about race, barriers to computing, and belonging in computing reveals something important about the disconnect between identifying the issue of underrepresentation and initiating efforts to alleviate it.

<u>Limitations</u>

There are a few limitations to note. Given the nature of some of the responses to the quantitative survey, the participant race may change the interpretation of the result. For example, items that asked respondents to reflect on how they believe their race affects them in computing are best understood at the aggregate if the sample is first disaggregated by race. This poses a challenge for consistent scaling of interpretation of survey responses for those items. In addition, the survey was developed based on theory and literature from a U.S. context. The comparability of concepts of race and racial discrimination may vary based on participants' countries of origin and residence. Further exploration in qualitative interviews and cultural validation will provide more insight into the replicability of results in other contexts. For the qualitative instrument, ensuring interviewers completed the interviews with enough probing where appropriate was of importance. The research team is developing detailed interviewer training and repeated reviews of practice interviews as appropriate.

Finally, the goal of the quantitative survey instrument was to understand how computing undergraduates make sense of race and racial (under)representation in computing. Questions were exploratory in nature and capture a number of factors relevant to race in computing. Future work may focus on one or more of these factors as a reliable measure of a facet of race in computing. Such work would likely require confirmatory factor analysis and could use this exploratory factor analysis as a guide.

CONCLUSION

This work-in-progress paper presents the design and testing of a quantitative and qualitative instrument as part of a mixed-methods study to understand perceptions of race among undergraduates in computing departments. To the best of our knowledge, these instruments are the first of their kind that are focused on computing undergraduates across a broad range of identities, institutions, institution types, and geographical locations.

These instruments will ultimately allow for capturing nuanced perceptions of race that will help to inform the greater computing and STEM community. Ultimately, this instrument can be extended to students across STEM majors, which will inform how departments design and implement activities and courses that help to create and foster more equitable and inclusive academic environments for students from racial groups that are historically underrepresented in computing. Future work includes not only collecting and analyzing responses to the instrument, but also extending it to computing graduate students, faculty, and staff, as well as (eventually) non-computing STEM disciplines.

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REFERENCES

[1] S. Zweben and B. Bizot, “2020 Taulbee Survey,” 2020. [Online]. Available: https://cra.org/wp-content/uploads/2021/05/2020-CRA-Taulbee-Survey.pdf
[2] E. W. Huff *et al.*, “Going Through a Process of Whitening: Student Experiences Within Computer Science Education,” in *Proceedings of the 52nd ACM Technical Symposium on Computer Science Education*, in SIGCSE ’21. New York, NY, USA: Association for Computing Machinery, Mar. 2021, p. 1348. doi: 10.1145/3408877.3432497.
[3] S. Erete, Y. A. Rankin, and J. O. Thomas, “A method to the madness: Applying an intersectional analysis of structural oppression and power in HCI and design,” *ACM Transactions on Computer-Human Interaction*, 2022.
[4] S. T. Jones and natalie araujo melo, “We Tell These Stories to Survive: Towards Abolition in Computer Science Education,” *Can. J. Sci. Math. Techn. Educ.*, vol. 21, no. 2, pp. 290–308, Jun. 2021, doi: 10.1007/s42330-021-00158-2.
[5] Z. O. Dunivin, H. Y. Yan, J. Ince, and F. Rojas, “Black Lives Matter protests shift public discourse,” *Proceedings of the National Academy of Sciences*, vol. 119, no. 10, p. e2117320119, Mar. 2022, doi: 10.1073/pnas.2117320119.
[6] K. D. Joshi, E. Trauth, L. Kvasny, A. J. Morgan, and F. C. Payton, “Making Black Lives Matter in the Information Technology Profession,” vol. 48, no. 2, 2017.

[7] F. C. Payton, L. Yarger, and V. Mbarika, “Black Lives Matter: A perspective from three Black information systems scholars,” *Information Systems Journal*, vol. 32, no. 1, pp. 222–232, 2022, doi: 10.1111/isj.12342.
[8] K. Lajtha and S. Saini, “Biogeochemistry statement on #ShutDownSTEM and Black Lives Matter,” *Biogeochemistry*, vol. 149, no. 3, pp. 237–237, Jul. 2020, doi: 10.1007/s10533-020-00682-7.
[9] “Researchers around the world prepare to #ShutDownSTEM and ‘Strike For Black Lives’.” https://www.science.org/content/article/researchers-around-world-prepare-shutdownstem-and-strike-black-lives (accessed Jan. 29, 2023).
[10] B. A. Burt, A. McKen, J. Burkhart, J. Hormell, and A. Knight, “Black Men in Engineering Graduate Education: Experiencing Racial Microaggressions within the Advisor–Advisee Relationship,” *The Journal of Negro Education*, vol. 88, no. 4, pp. 493–508, 2019.
[11] Y. A. Rankin, J. O. Thomas, and S. Erete, “Black women speak: Examining power, privilege, and identity in CS education,” *ACM Transactions on Computing Education (TOCE)*, vol. 21, no. 4, pp. 1–31, 2021.
[12] E. O. McGee and D. O. Stovall, *Black, Brown, Bruised: How Racialized STEM Education Stifles Innovation*. Cambridge, Massachusetts: Harvard Education Press, 2020.
[13] D. Dortch and C. Patel, “Black undergraduate women and their sense of belonging in STEM at predominantly White institutions,” *NASPA Journal About Women in Higher Education*, vol. 10, no. 2, pp. 202–215, 2017.
[14] E. McGee, “‘Black Genius, Asian Fail’: The Detriment of Stereotype Lift and Stereotype Threat in High-Achieving Asian and Black STEM Students,” *AERA Open*, vol. 4, no. 4, p. 2332858418816658, Oct. 2018, doi: 10.1177/2332858418816658.
[15] M. Dancy, K. Rainey, E. Stearns, R. Mickelson, and S. Moller, “Undergraduates’ awareness of White and male privilege in STEM,” *International Journal of STEM Education*, vol. 7, no. 1, p. 52, Oct. 2020, doi: 10.1186/s40594-020-00250-3.
[16] A. E. Martin and T. R. Fisher-Ari, “‘If We Don’t Have Diversity, There’s No Future to See’: High-school students’ perceptions of race and gender representation in STEM,” *Sci Educ*, vol. 105, no. 6, pp. 1076–1099, Nov. 2021, doi: 10.1002/sce.21677.
[17] J. Goode, S. R. Johnson, and K. Sundstrom, “Disrupting colorblind teacher education in computer science,” *Professional Development in Education*, vol. 46, no. 2, pp. 354–367, Mar. 2020, doi: 10.1080/19415257.2018.1550102.
[18] D. M. Sparks and K. Pole, “‘Do we teach subjects or students?’ Analyzing science and mathematics teacher conversations about issues of equity in the classroom,” *School Science and Mathematics*, vol. 119, no. 7, pp. 405–416, 2019, doi: 10.1111/ssm.12361.
[19] T. Russo-Tait, “Color-blind or racially conscious? How college science faculty make sense of racial/ethnic underrepresentation in STEM,” *J Res Sci Teach*, p. tea.21775, Apr. 2022, doi: 10.1002/tea.21775.
[20] A. D. Robertson, V. Vélez, W. T. Hairston, and E. Bonilla-Silva, “Race-evasive frames in physics and physics education: Results from an interview study,” Forthcoming.
[21] K. Crenshaw, *On Intersectionality: Essential Writings*. The New Press, 2022.
[22] B. Blaser and R. E. Ladner, “Why is Data on Disability so Hard to Collect and Understand?,” presented at the 2020 Research on Equity and Sustained Participation in Engineering, Computing, and Technology (RESPECT), IEEE, 2020, pp. 1–8.

[23] E. Bonilla-Silva, “Detroit Area Study, 1998: White Racial Ideology,” Inter-university Consortium for Political and Social Research [distributor], Jan. 2010. [Online]. Available: https://doi.org/10.3886/ICPSR26261.v1
[24] “Factor Retention Decisions in Exploratory Factor Analysis: a Tutorial on Parallel Analysis - James C. Hayton, David G. Allen, Vida Scarpello, 2004.” https://journals.sagepub.com/doi/10.1177/1094428104263675 (accessed Feb. 06, 2023).
[25] M. Tavakol and R. Dennick, “Making sense of Cronbach’s alpha,” *Int J Med Educ*, vol. 2, pp. 53–55, Jun. 2011, doi: 10.5116/ijme.4dfb.8dfd.
[26] I. B. Ira H. Bernstein Jum Nunnally, *Psychometric Theory: 3rd (Third) edition*. McGraw-Hill Companies, The, 1994.
[27] S. Zweben and B. Bizot, “2021 Taulbee Survey: CS Enrollment Grows at All Degree Levels, With Increased Gender Diversity,” Computing Research Association, May 2022. [Online]. Available: https://cra.org/wp-content/uploads/2022/05/2021-Taulbee-Survey.pdf
[28] D. Napitupulu, J. A. Kadar, and R. K. Jati, “Validity Testing of Technology Acceptance Model Based on Factor Analysis Approach,” *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 5, no. 3, Art. no. 3, Mar. 2017, doi: 10.11591/ijeecs.v5.i3.pp697-704.
[29] H. F. Kaiser, “The application of electronic computers to factor analysis,” *Educational and Psychological Measurement*, vol. 20, pp. 141–151, 1960, doi: 10.1177/001316446002000116.
[30] M. J. Chang, J. Sharkness, S. Hurtado, and C. B. Newman, “What matters in college for retaining aspiring scientists and engineers from underrepresented racial groups: RETAINING ASPIRING SCIENTISTS,” *J Res Sci Teach*, vol. 51, no. 5, pp. 555–580, May 2014, doi: 10.1002/tea.21146.
[31] K. Rainey, M. Dancy, R. Mickelson, E. Stearns, and S. Moller, “Race and gender differences in how sense of belonging influences decisions to major in STEM,” *IJ STEM Ed*, vol. 5, no. 1, p. 10, Apr. 2018, doi: 10.1186/s40594-018-0115-6.
[32] P. L. Carter, R. Skiba, M. I. Arredondo, and M. Pollock, “You Can’t Fix What You Don’t Look At: Acknowledging Race in Addressing Racial Discipline Disparities,” *Urban Education*, vol. 52, no. 2, pp. 207–235, Feb. 2017, doi: 10.1177/0042085916660350.