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On Measuring Cultural Competence: Instrument Design and Testing

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Dr. Grady advocates increasing the number of women and minorities in computer science. She believes that "the STEM workforce has both gender disparities and that of historically disenfranchised groups. As an AAAS IF/THEN ambassador, she affects change by examining girls' perceptions, attitudes, and behaviors, helping them gain confidence in curating and developing a STEM identity."

Additionally, Dr. Grady has been featured in museums throughout the nation, has spoken at national and international conferences, serves on multiple boards, and was featured as a statue in the world's largest exhibit of women's statues. Technology is the way of the future, and Dr. Grady has a vision for minority girls' and women's futures. She realizes that vision by providing educational opportunities through community organizations, philanthropic efforts, college courses, and research grants and publications.

She currently holds the following Quality Matters Certifications: Master Reviewer, Peer Reviewer, Accelerated Designing Your Online Course F2F Facilitator, Accelerated Improving Your Online Course F2F Facilitator, Reviewer Course for Program Reviews, and Applying the QM Rubric Face to Face Facilitator.

She is a board member of the Winston-Salem State University Foundation, National Girls Collaborative Project, American Association for the Advancement of Science National Conference of Lawyers and Scientists, an advisory member for Nvolve, Inc, and several grants. She is also a member of several associations, including the Alpha Zeta Omega Chapter of Alpha Kappa Alpha Sorority, Inc., Junior League of Durham and Orange Counties, Winston Salem State University National Alumni Association (life member), and North Carolina Central University National Alumni Association (life member). She also volunteers for various organizations, including Boy Scouts of America, FIRST North Carolina, Girl Scouts of America, and Black Girls Code, which introduces science, technology, engineering, and mathematics skills to African American girls.

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INTRODUCTION

This research paper presents a novel instrument that quantitatively measures the cultural competence of students in university computing departments. Cultural competence first emerged in social work [1] and counseling psychology [2] as:

> “(A) set of congruent behaviors, attitudes, and policies that come together in a system, agency, or among professionals and enable that system, agency, or those professionals to work effectively in cross-cultural situations.”

The representation of students from minoritized groups in computing based on race, ethnicity, gender, sexuality, ability, and socioeconomic status remains low [3], [4]. While research indicates that technical employees from minoritized groups cite unfairness as the leading factor for leaving a company and/or the industry [5], university computing departments often replicate these same types of environments (e.g., microaggressions; being forced to work alone in study/research groups; being ignored by faculty, teaching assistants, and peers; and credit being taken for their work), resulting in high attrition rates [2], [6]–[11].

Most efforts to broaden participation in CS center students from minoritized groups via deficit-based strategies [12], such as affinity groups, mentoring, and bridge/training programs. This forces students to (re-)enter the same harmful environments with the expectation of developing enough “grit” to “persist” [13]. These efforts place the responsibility on the most minoritized, with no focus on those from dominant identities who create/enable these environments. Creating and sustaining more equitable and inclusive environments requires improving everyone’s cultural competence (not just increasing sense of belonging and self-efficacy in those who are most harmed).

As more computing departments develop interventions to increase diversity, equity, and inclusion that target all students [2], [14], an instrument for measuring their impact beyond enrollment, retention, and graduation rates is needed. This work details the development and testing of an instrument for measuring cultural competence in the context of how identity impacts and is impacted by academic computing environments. The tool can be administered by faculty and staff and used within a single group (e.g., course, workshop/training, department). Results indicate construct validity and internal consistency were demonstrated.

RELEVANT WORK

According to [1], a culturally competent system, agency, or institution includes the following constructs: *valuing diversity*, *cultural self-assessment*, *consciousness of the dynamics of difference*, *institutionalized cultural knowledge*, and *adaptations to diversity*. More recent literature uses four key constructs [15], [16], which we map to the original five (in parentheses): attitude (*valuing diversity*), awareness (*cultural self-assessment*), skills (*consciousness of the dynamics of difference* and *adaptations to diversity*), and knowledge (*institutionalized cultural knowledge*).

Disciplines such as social work, counseling, and healthcare provide student training to develop and improve cultural competence, because graduates are expected to effectively render services to clients and patients from all identities, especially vulnerable populations [17]–[25]. An inability to do so can result in situations that range from uncomfortable to life-threatening for recipients. The most widely used instruments contain 20-40 items [26], use a Likert scale (four- to seven-point), and have varying response options (e.g., very inaccurate to very accurate, strongly disagree to strongly agree) and scoring approaches.

While CS graduates do not work directly with clients and patients, the technologies they develop also directly impact people (especially vulnerable populations) in ways that range from uncomfortable to life-threatening (e.g., recidivism [27], healthcare [28], and voice-recognition software [29], as well as rideshare apps [30], [31]). These biased technologies are often attributed to the lack of diverse technical development teams [12].

The shifting focus on identity in computing has increased the number of postsecondary interventions available (e.g., courses, workshops, and training) [32], [33]. However, to the best of our knowledge, there is no instrument to measure the impact of these interventions on cultural competence. According to cseducationresearch.org (a repository of all CS education-related surveys), the overwhelming majority of instruments measure student interest in, attitudes toward, and self-efficacy related to pursuing courses and degrees [34].

Limitations of Cultural Competence Instruments

Several limitations with current instruments that measure cultural competence render them impractical for adoption in computing [26]. First, most instruments narrowly define "culture" to include only race and ethnicity. This exclusion of other parts of one's identity that are the most salient and lead to "othering" (e.g., gender, sexuality, socioeconomic status, and ability) ignores additional forms of oppression experienced by people from different identities and intersectionality [35]–[37].

Second, most instruments assume that culture is an attribute that only those who are ethnic or racialized "others" possess [26], thus presenting it as a deficit. Evidence of this is discussed in [38], [39], where white American identity is described as the invisible norm or nothingness "on which all others are made aberrant." Given the implication that whiteness is the standard, existing measures "rarely acknowledge or examine dominant cultures" [26], thus ignoring more nuanced results based on all parts of participant identities.

Third, most instruments center the respondent's knowledge about "others" as the primary indicator of cultural competence, with few (if any) indicators describing the respondent's self-awareness and applications of any obtained knowledge in practice. In computing, this lack of self-awareness is exemplified in notions of technology and people being "neutral" or "colorblind" [40]. However, the dangers of neutrality in technology and people have been discussed at length in social science [1], [38], [41]–[44].

Fourth, most instruments assume cultural incompetence is due to individual respondents' discriminatory attitudes towards "others," without consideration of the structural and systemic inequalities/inequities that have privileged some at the expense of others [26]. Those only considering individual actions, without recognizing the systemic/structural barriers impacting others, lead to overconfidence of one's cultural competence.

Finally, prior instruments were situated in contexts that render them too discipline-specific for use with computing students. Based on the bourgeoning need in computing and lack of available instruments, the goal of this study was to design and validate an instrument to measure the cultural competence of computing students. While it is not an intervention, the instrument could be used to measure the impact of interventions (e.g., courses, modules, teaching assistant training, and other department activities) in longitudinal studies.

METHODS

Instrument Development

First, a review of the literature on cultural competence and existing instruments was completed. Given the lack of computing-related instruments, the review primarily focused on commonly used ones in nursing, healthcare, and counseling psychology [16]–[24], [26]. Specifically, items were reviewed for descriptions and themes addressed. Common themes (e.g., beliefs related to diversity, equity, and inclusion) were used to develop a computing instrument across multiple phases that included relevant topics from prior identity-related computing instruments, but from a non-personal perspective. For example, while prior surveys included items related to a respondent's sense of belonging (e.g., "I often feel included in classes") [45], the new instrument included items related to a respondent's belief that sense of belonging is important for academic/professional success (e.g., "It is important for everyone to feel like they belong in a class, department, or university").

In phase 1, a 42-item instrument was developed and distributed, where each item was mapped to the five constructs of cultural competence in [1] (Table 1). Responses were collected on a four-point Likert scale (Strongly Agree, Agree, Disagree, Strongly Disagree) to eliminate ambiguity. Following phase 1 analysis, the instrument was updated to 27 items and distributed for another round of data collection. Following phase 2 analysis, the instrument was updated to 22 items. Responses were collected via Google Forms.

Table 1: Phase 1 instrument items.

Valuing Diversity

1. It's important for every student to feel like they belong in a class, department, or university.
2. Having a diverse class and department is important to me.
3. It's important to be around people from different cultures.

4. I always intervene when I observe discrimination occurring.
5. People should speak their native language in the U.S, if that's what makes them comfortable.
6. I am comfortable when I'm one of the few, if not the only person who looks like me in a group of people.

Cultural Self-Assessment

1. When it comes to race/ethnicity, I don't see color.
2. Certain races/ethnicities are naturally better at computing than others.
3. Certain genders are naturally better at computing than others.
4. I prefer to work with classmates who look like me.
5. Everyone has the same opportunities to succeed. If they don't, then they just didn't work hard enough.
6. I don't believe that any race, ethnicity, or gender has any "privilege."
7. I feel like diversity, equity, and inclusion are forced on me.

Consciousness of the Dynamics of Difference

1. If people from different identities communicate differently than I do (e.g., body language or verbal), then I prefer not to communicate with them.
2. I believe people from groups that are historically underrepresented (e.g., Black, Latinx, and Native American) often are too angry or disrespectful when communicating.
3. If someone from a different identity disagrees with me when discussing issues related to their identity, then they are wrong.
4. I often refer to faculty who are men as "Mr." or by first name.
5. I often refer to faculty who are women as "Miss," "Ms.," or "Mrs." or by first name.

Institutionalized Cultural Knowledge

1. I understand that there are different types of diversity (e.g., race, ethnicity, gender, religion, sexuality, ability, etc.).
2. I understand the difference between race and ethnicity.
3. I always report any discriminatory behavior and posts I encounter on social media.
4. There are technologies that are biased against some identities.
5. I understand the differences between diversity, equity, and inclusion.
6. I think a one-hour workshop or training on diversity, equity, and inclusion is sufficient to improve environments.
7. I understand that people have identities that intersect with their race/ethnicity (e.g., gender, sexuality, ability, etc.) that impact their experiences.
8. I understand that different historical experiences of people from groups that are historically underrepresented (e.g., Black, Latinx, and Native American) may negatively impact their experiences in computing.
9. I understand that discrimination and stereotypes are dehumanizing and can incite violence against people based on their identity.

Adaptations to Diversity

1. Prior to college, I was regularly in environments with people from different identities.
2. My computing courses are not diverse enough.
3. My computing department is not diverse enough.
4. I am comfortable discussing identity with people who don't look like me.
5. I want to learn more about different cultures.
6. I would like to have more department activities and courses that help understand various cultures.
7. I would like to do more to ensure that everyone feels they belong in my classes, department, and university.
8. I understand that certain words and statements can be offensive to people from different identities.
9. My beliefs and perspectives regarding different identities may be limited, due to my limited exposure to people who don't look like me.
10. I try to learn cultural protocols and practices when communicating with people from different cultures.
11. I ask people from different cultures for help learning about their cultures.
12. If someone tells me that I said something insensitive or offensive based on their identity, then I always apologize and make amends, even if I didn't mean to offend.

Data Collection Process

The target population was students completing university computing courses. This was not restricted to students majoring in CS, as its interdisciplinary nature requires other majors to complete at least one CS course for degree requirements. IRB approval was received prior to data collection. Data collection was implemented across the 2019-20 (phase 1) and 2020-21 (phase 2) academic years. Participants were solicited via email through faculty, who were first sent an introductory email explaining the purpose of the study and request to distribute the survey. Potential participants were emailed the informed consent form detailing the purpose of the study and link to begin. A total of 337 and 301 respondents fully completed the survey in phases 1 and 2, respectively. The data collected was exported into a CSV file for analysis via RStudio.

Data Analysis and Instrument Validation

Instrument validation consisted of the following steps in each phase. First, the internal consistency of the items was determined via Cronbach's α [46]. Item-to-item and item-to-total correlations were then examined to identify multicollinearity and assess the relationships between each item and the overall scale. Next, principal component analysis (PCA) was used to determine the number of latent dimensions present. Since all items were measured on the same Likert scale (1: Strongly Disagree to 4: Strongly Agree), the PCA was performed on the variance-covariance matrix. The Kaiser criterion (eigenvalues>1) and scree test were combined to identify the optimal number of factors [47].

Principal axis factoring (PAF) further explored underlying data structures [48]. Since it was expected that the factors would be highly correlated, an oblique rotation (direct oblimin, allowing for between-factor correlations) was used to produce more meaningful data interpretations. The identified factors were then revised to remove items with low factor loadings. Internal consistency for each factor was determined using Cronbach's α.

After completing this process, the instrument was revised to remove/add items and rephrase current ones for clarity and better alignment within the identified factor. The revised instrument was distributed and, following data collection, analysis was repeated. The results of the second testing phase (factors and items loaded) became the final version.

The following criteria were defined to guide instrument validation. First, items with item-to-total correlations below 0.32 [49] were omitted. The minimum acceptable internal consistency (as determined by Cronbach's α) was 0.6-0.7 [49]. The minimum cumulative variance that the number of components should explain was 50%. While this is lower than the traditional 70-80% window, this high a range is often unattainable in more social science-based research (whose cumulative variance is usually in the range of 50-60%) [50].

RESULTS

Study Sample

In phase 1, 54% of all respondents were enrolled at Predominately White Institutions (PWIs) and 46% at Historically Black Colleges and Universities (HBCUs). Approximately 50% of the respondents were from an ethnoracial group that is historically underrepresented in computing, 41% were white or Asian, and 7% were multiracial. Approximately 64% of respondents were women, 34% were men, and 2% were non-binary. Majority of the respondents were computing majors (59%), while 41% were non-computing majors enrolled in courses required for their major.

Note that this study oversampled across participant racial and gender identities. Approximately 70% of all computing graduates identify as white and Asian, and 80% identify as men [3]. Using a sample representative of the discipline would result in an instrument that not only did not accurately reflect participants who are neither white, Asian, or men, but also would not accurately reflect the nuance within minoritized groups. For example, Black computing undergraduates attending an HBCU may have differing academic experiences (as part of the dominant racial group on campus) from those attending PWIs (who are part of a non-dominant group both in computing and on campus). Students may also be part of a non-dominant group (e.g., race) and dominant group (e.g., gender or ability) based on different parts of their identity. In addition, Cross et al. [1] note that because people from non-dominant identities are also "trained in the dominant society's frame of reference, they may only be a little more competent in cross-cultural practice" than their counterparts.

Oversampling also occurred in terms of institution type. While PWIs produce the most computing graduates, the impact of minority-serving institutions on student cultural competence cannot be ignored. However, no Tribal Colleges and Universities offered a four-year computing degree at the time of instrument development. In addition, the designation of Hispanic-Serving Institution (HSI) is given to schools based on the percentage of Hispanic/Latinx students enrolled (not because the institution was founded to serve Hispanic/Latinx students or offer programs that support them). As a result, HBCUs (established to serve Black students) are oversampled to represent minority-serving institutions, as these often include differing identity-related experiences.

In phase 2, 57% of respondents were enrolled at PWIs and 43% at HBCUs. Approximately 43% were from an ethnoracial group that is historically underrepresented group, 47% were white or Asian, and 11% were multiracial. Approximately 57% of respondents were women, 40% were men, and 3% were non-binary. Majority of the respondents were computing majors (57%), and 43% were non-majors enrolled in required computing courses.

Exploratory and Confirmatory Factor Analysis Results

Exploratory Factor Analysis: Phase 1

Analysis of the instrument was performed on 39 items (excluding three demographic items). Internal consistency (based on the original five constructs) was low, following drop-one Cronbach's α, and not all items loaded as expected. PCA was then used to identify five principal components (factors), which accounted for approximately 51% of the cumulative variance. Using PAF with oblique rotation, 25 of the 39 items loaded onto the five factors determined by PCA. Table 2 presents the 25 items that loaded following PAF.

Table 2: Phase 1 instrument items (following principal axis factoring).

Factor 1

1. I understand the differences between diversity, equity, and inclusion.
2. I always intervene when I observe discrimination occurring.
3. I always report discriminatory behavior (including work and social media).
4. I am comfortable discussing identities (e.g., race, ethnicity, sexuality, and gender) with people who don't look like me.
5. If someone tells me that I offended them based on their, then they usually just misunderstood what I meant.
6. Certain words/statements that may not offend me may offend others with different identities.

7. I try to learn cultural protocols/practices when communicating with people from different identities.
8. I want to learn more about different identities.
9. I ask people from different identities for help learning more about their identities/experiences.
10. I would like to have more department activities/courses that help understand various identities.
11. People have identities that intersect with their race (e.g., gender, sexuality, religion, etc.), which also impact their experiences in classes and society.
12. Stereotypes are dehumanizing and can lead to discrimination or violence against people based on their identity.
13. I would like to do more to ensure that everyone feels they belong in my classes, department, and university.

Factor 2

1. There are many ways to define diversity.
2. Having a diverse class and department are important to me.
3. It is important to be around people with different identities (e.g., race, ethnicity, gender, class, religion, sexuality, ability, etc.).
4. It is important for students to feel they belong in a class, department, or university.
5. I understand the difference between race and ethnicity.

Factor 3

1. When it comes to race, I don't see color.
2. Everyone has the same opportunities to succeed. If they don't, then they just didn't work hard enough.
3. I don't believe that any race, ethnicity, or gender has any privilege.

Factor 4

1. My computing courses are not diverse enough.
2. My computing department is not diverse enough.

Factor 5

1. I often refer to professors who are men as "Mr." or by first name.
2. I often refer to professors who are women as "Miss," "Ms.," or "Mrs." or by first name.

Factor 1 included 13 items (majority of which originally mapped to *consciousness of the dynamics of difference* and *adaptations to diversity*). Factor 2 included five items (majority of which mapped to *valuing diversity* and *institutionalization of cultural knowledge*). Factor 3 included three items (which mapped to *cultural self-assessment*). Factor 4 included two items that mapped to *adaptations to diversity*. Factor 5 also included two items that mapped to *consciousness of the dynamics of difference*. The internal reliabilities (according to Cronbach's α) for Factors 1, 2, 3, 4, and 5 were 0.85, 0.83, 0.64, 0.87, and 0.87, respectively.

The 25 items of Table 2 did not correspond directly to the same groupings from Table 1. The only factor with a 1:1 mapping between an original construct and factor was Factor 3 (*cultural self-assessment*). In addition, the internal reliability of Factor 3 (0.64) was the only one that was less than 0.7. Finally, Factors 4 and 5 both had only two items load onto them.

Items were added to Factors 4 and 5 to ensure a minimum of three items in phase 2 distribution and eliminate ambiguity. The item "My non-computing courses are not diverse enough" was added to Factor 4. The items "I often refer to professors who are women as 'Miss,' 'Ms.,' or 'Mrs.,' or by first name" and "I often refer to professors who are men as 'Mr.' or by first name) in Factor 5 were originally intended to capture the differences in how faculty of different genders are addressed in academia [51]. However, based on open-ended responses from participants, it was determined that this was too ambiguous. Additionally, this did not account for faculty who did not use binary gender definitions. To remove ambiguity (and be more gender-inclusive), these items were replaced with "It's not that serious for faculty to require students to refer to them as Dr. or Professor" (which was intended to account for how some faculty require proper titles while others don't). To ensure a minimum of three items in this factor (and account for more negatively coded items), the following two items were added: "It's too confusing to remember someone's pronouns" and "I'd rather use someone's nickname if their name is too difficult to pronounce." All item descriptions were revised to more broadly encompass identity as originally intended and better align with new factor and loaded items. For example, "I want to learn more about different cultures" was revised to "I want to learn more about different identities."

Exploratory Factor Analysis: Phase 2

The revised, 28-item instrument (including demographic data) had an overall Cronbach's α of 0.84. With the drop-one Cronbach's α ranging between 0.83 and 0.84, no items were deleted as unreliable. Item-to-item and item-to-total correlations were reviewed to check for multicollinearity and assess the relationships between each item and the overall scale. Three items were omitted due to low item-to-total correlations (below 0.32). The remaining item-to-total correlations were between 0.32 and 0.63. Item-to-item correlations did not suggest any issues with multicollinearity (item-to-item correlations < 0.8), and no other items were dropped. The results of the PCA identified four factors that explained 51% of the cumulative variance. Figure 1 presents the scree plot and the eigenvalues.

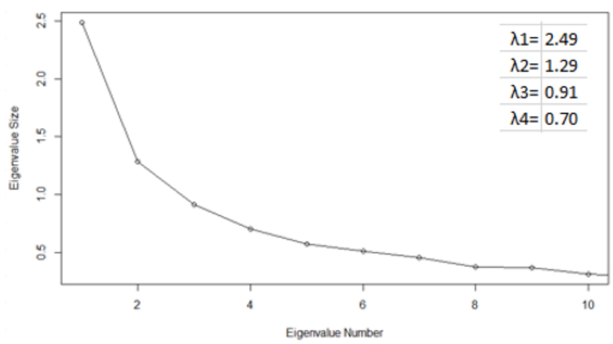

Figure 1: Scree plot of eigenvalues.

After performing PAF with oblique rotation, a four-factor data structure was confirmed, with a total of 22 items loading on them. Table 3 presents the items that loaded, by factor. One item cross-loaded across Factors 1 and 2: "There are many ways to define diversity." This item was moved to Factor 1, based on better alignment with other items loading onto this factor. The internal consistency for the 22-item scale was 0.85. The internal consistency for the four subscales ranged between 0.75 and 0.82. Item descriptions, drop-one Cronbach's α, and factor loadings are presented in Table 3, with the final construct mapped to each factor. Item descriptions were revised to remove additional ambiguity following phase 2 analysis.

Table 3: Subscale descriptions, factor loadings, and reliability following phase 2 principal axis factoring.

	Factor loading	Cronbach's α
Factor 1: Skills (α = 0.75, mean = 3.67)		
1. I try to learn cultural protocols/practices when communicating with people from different identities.	0.704	0.69
2. I search for opportunities to learn more about different identities.	0.618	0.71
3. We should have more department activities/courses to learn about various identities.	0.579	0.71
4. I engage in conversations with people from different identities to learn more about their experiences.	0.522	0.72

5. I regularly discuss topics of identity (including forms of discrimination and oppression) within my social circle.	0.429	0.74
6. I always report discriminatory behavior (including work and social media).	0.412	0.74
7. I always intervene when I observe discrimination occurring.	0.365	0.73
Factor 2: Attitude (α = 0.82, mean = 3.67)		
1. Stereotypes are dehumanizing and can lead to discrimination or violence against people based on their identity.	0.800	0.78
2. Certain words/statements that may not offend me may offend others with different identities.	0.581	0.80
3. I can discuss intersectionality and its importance.	0.463	0.80
4. It is important to learn about/understand different identities.	0.458	0.80
5. It is important for everyone (students, faculty, and staff) to feel they belong in a class, department, or university.	0.420	0.82
6. There are many ways to define diversity.	0.481	0.81
7. I actively work to ensure that everyone feels they belong in my classes, department, and university.	0.449	0.79
8. Having a diverse class and department are important.	0.393	0.81
Factor 3: Self-Awareness (α = 0.76, overall mean = 1.66)		
1. When it comes to race, I don't see color.	0.693	0.73
2. Everyone has the same opportunities to succeed. If they don't, then they just didn't work hard enough.	0.565	0.74
3. I don't believe that any race, ethnicity, or gender has any "privilege."	0.691	0.68
4. If someone tells me that I offended them based on their identity, then they usually just misunderstood what I meant.	0.703	0.67
Factor 4: Knowledge (α = 0.80, overall mean = 3.22)		
1. ~~It's not that serious for faculty to require students to refer to them as Dr. or Professor.~~ Faculty who require students to refer to them as Dr. or Professor are being too strict.	0.931	0.61
2. I'd rather give someone a nickname if their name is too difficult to pronounce.	0.831	0.65
3. It's too confusing to remember someone's pronouns.	0.516	0.89

Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) was used to verify the factor structure and test the relationship between observed variables and their underlying latent constructs. CFA was performed using the final items from Table 3 and a new set of respondents that consisted of 220 faculty members from computing departments nationwide. The R package lavaan [52] was used for estimation, and the full four-factor model produced appropriate measures of the goodness of fit.

The comparative fit index (CFI) and the Tucker-Lewis index (TLI) were 0.939 and 0.930 respectively, both close to the suggested threshold of 0.95 [53]. The root mean square error of approximation (RMSEA) of 0.053 was in the desired range (below 0.06), which indicates a good fit [54]. All the coefficient estimates in the full model were statistically significant at 0.01 significance level, and all the indicator error variances were positive. Most of the factor loadings from the CFA were close to or above 0.7, which indicates an adequate magnitude of the relationship between the latent constructs and the items that are designed to measure them. Since the results of the CFA did not warrant model respecification, the measures of internal consistency remained the same, with Cronbach's α for the four constructs ranging between 0.60 and 0.71, and the overall instrument statistic of 0.85.

DISCUSSION

While the original instrument was designed to align with the five constructs of cultural competence defined by [1], the results of phase 2 testing provided strong evidence supporting a four-factor model that aligned with more recent work [15], [16]. Given how items loaded, the construct names for each factor were also revised: Factor 1 better aligned with Skills; Factor 2 with Attitude; Factor 3 with Self-Awareness; and Factor 4 with Knowledge.

Phase 1 analysis included more items with factor loadings less than 0.4 [49]. However, the revision of items and the addition of new ones for phase 2 resulted in only two items with factor loadings less than 0.4 (Factors 1 and 2). Given their loading close to 0.4 and alignment with the construct, these two were maintained. The items loading within each factor aligned well in terms of what the factor intended to measure. Items in Factor 3 (Self-Awareness) loaded onto the corresponding factor in both phases of analysis. Factors 1 and 2 (Skills and Attitude) include more items than Factors 3 and 4 (Self-Awareness and Knowledge). Since completion of the instrument results in a score, careful consideration is required for proper weighting of items before distributing the survey.

Open-ended comments in phase 2 were primarily related to Factor 4 (Knowledge), Item 1 ("It's not that serious for faculty to require students to refer to them as Dr. or Professor"), which was identified as confusing. We attributed this lack of clarity to the lower Cronbach's α and revised the item to "Faculty who require students to refer to them as Dr. or Professor are being too strict." We also maintained this item because of the important nuance that is captured (including experiences of faculty from minoritized groups who have reported being referred to by first name or not as faculty versus faculty from non-minoritized groups who sometimes note they do not care how students address them [51], [55]). In addition, examples of identities to consider (e.g., race, gender, sexuality, ability, and class) were removed from most items, and definitions of identity, diversity, equity, and inclusion were provided at the beginning of the assessment for clarity and to minimize text.

The items in the final version of the instrument (Table 3) are not specific to the computing discipline, which was part of the original goal of the instrument design: application across a range of STEM disciplines, if possible. As a result, the items extend beyond the discipline and into personal ideologies and understanding of systemic/structural issues impacting people from different identities. Given the goodness of fit when using faculty responses for CFA, this survey is being extended to the analysis of computing faculty as well as K-12 educators as part of future work.

Demographic data on institution type, gender identity, classification, and disability status were included in the final version of the instrument. While this will provide meaningful insight into participant responses to the final instrument, we do not consider those here, as this work was limited to the design and validation of the instrument.

CONCLUSION AND FUTURE WORK

As computing becomes more ubiquitous, it is important that those developing the technologies have a level of cultural competence that not only eradicates the harmful/biased technologies that currently exist, but also ensures they are never created. This also requires creating more inclusive and equitable academic/professional environments for people of all identities. Given the impacts of technology on the health, safety, and well-being of users (especially those from vulnerable populations), it is important that computing departments better understand, develop, and improve the cultural competence of their students and graduates.

Motivated by the work in counseling psychology, social work, and healthcare, this instrument was developed to quantitatively measure individual cultural competence of computing students. The instrument was tested over two academic years, with results demonstrating that the final instrument construct validity and internal consistency. While it is not an intervention itself, the instrument can be an important tool for measuring the impact of interventions in university computing departments, especially longitudinal studies (e.g., pre/post-assessments). In addition, the discipline-independent design of the instrument makes it easier to extend to other STEM disciplines.

We consider this instrument to be an initial version. Thus, we are consistently looking to improve it and address limitations. For example, the current survey does not include items related to ableism in computing environments. Given the lack of disability-related data collection, this is important to address in the next version of the instrument. Second, the recruitment of students from two-year colleges and other minority-serving institutions will be incorporated into distribution of the instrument for data collection and analysis. Next, we will extend validation and testing of the instrument on students in non-computing STEM disciplines to confirm generalizability.

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