Quantifying Disparities in Computing Education: Access, Participation, and Intersectionality

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ABSTRACT

Quantitative research in CS education has suffered from inattention to complexities inherent in measuring educational equity. This study aims to tease apart the complexities of educational equity and advance the field by developing a disparity index for quantifying inequities and using it to investigate the importance of accounting for intersectionality and distinguishing between access to and participation in CS education. This descriptive study analyzed student demographic and course-taking data for N=1,537,073 high school students in Texas. Results showed the disparity index can be a useful tool for quantifying and assessing equity in CS education. Disparities in terms of access to and participation in CS education were compounded for students who were members of multiple underrepresented subpopulations (e.g., rural Black females). Disparities differed between measures of access and participation. Implications of this study are that accounting for the intersectionality of students' multiple social identities and distinguishing between access and participation in quantitative measures are key to understanding (and thus addressing) the complexities of educational equity.

KEYWORDS

quantitative measures, broadening participation in computing, educational disparities, educational equity, access to computing education, intersectionality

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1 INTRODUCTION

Improving students' interest, participation, and overall learning experiences in CS has been an important endeavor within the CS education field in recent years. Researchers have discussed how the CS education pipeline has not been sufficient to meet the demands of today's digital economy [1-3]. High school CS courses do not reflect the diversity of today's student population with respect to gender, ethnicity, or socioeconomic status. Historically, students of color, females, and socioeconomically disadvantaged students have been consistently underrepresented in CS courses [4-6]. Even though there has been a notable increase in CS majors since 2009 [7], significant disparities continue to exist. The combination of structural and systemic forces that limit access, recruitment, and retention of students has exacerbated disparities in CS [8]. Furthermore, course offerings, teacher preparation, instructional resources, and the current education policy climate have also shaped the availability and quality of CS education opportunities for students [9].

Notwithstanding the multiple types of disparities that have been identified and reported, efforts to measure and track disparities in CS education have lacked guidance from quantitative research that similar efforts in other social science domains have received. Research in other disciplines have provided valuable insight on how to effectively measure disparities to improve access to quality healthcare [10-12], provide an equal distribution of school funds [13], and mitigate the disparate identification and treatment of children of color in the child welfare system [14] and in special education in schools [15]. Given the fact that CS education is rife with inequities for many student subgroups, it is imperative that the CS education research community follow the lead of these other disciplines by establishing standards and robust methods for measuring inequities.

The purpose of this study is to introduce a disparity index as a method for quantifying inequities in CS education and investigate how it can be used to assess issues of equity and intersectionality as they pertain to measures of access to and participation in CS education.

2 BACKGROUND

Measuring and addressing equity issues in education is a complex endeavor. Distinguishing between and differentially measuring issues of equity in access to CS and equity in participation in CS is also crucial to pinpointing areas of inequity in CS education and, in turn, determining how to address them. Further, understanding and accounting for the factors that contribute to disparities is challenging because of the intersectionality inherent in students' social identities. Isolating individual facets of students' identity for measurement, a common practice, does not tell the whole story of their

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experiences. Recognizing the significant role of intersectionality in our attempts to quantify disparity is essential to understanding the unique barriers that certain groups of students face. In our review of the literature, we discuss issues of equity in access and participation in CS education, the importance of intersectionality, and methods for quantifying educational disparities.

2.1 Equity in Access to and Participation in CS Education

Researchers have identified and quantified persistent gaps in access to CS courses in high school [2,8,16]. For example, the 2019 State of Computer Science Education report found that schools with larger percentages of minority students, schools with larger percentages of students from low socio-economic backgrounds, schools in rural areas, and Title 1 eligible schools are all less likely to offer CS courses for their students. In terms of participation, research has shown that females and underrepresented minority students are less likely to pursue CS degrees [17]. Identifying that these disparities in access and participation exist in CS education is a necessary first step in addressing the problem. But to understand whether we are making progress towards eradicating inequities in CS education, it is essential to be able to systematically measure and compare these disparities across school districts and over time.

2.2 Intersectionality

Intersectionality can be described as the social experience of individual identity as it is dynamically produced from mutually constitutive elements [18]. For example, a student may see herself as not just a female, but also a Latina, a sister, an athlete, and a musician. Understanding how these multiple identities converge to influence students' experiences is important for addressing equity issues in education.

Understanding intersectionality can assist in illuminating intersections that are often ignored. For example, ignoring intersections embodied by women and men of color, most studies on underrepresented minority groups in engineering undergraduate education focus on gender or on race/ethnicity separately. Some of these studies focus on White women [19, 20], while others aggregate students of color (i.e., Blacks, Hispanics/Latinos, and Native Americans) due to the small numbers in each group [21]. This is problematic, as these studies provide only a partial examination of students and erroneously imply that all minority students have similar pre-college background, college experiences, and ultimately college outcomes [22].

Taking intersectionality into account as we develop methods for quantifying disparity is critical. As we look to advance the ways in which we measure issues of equity in CS education, we must attend to the intersections in students' identities and allow these to be reflected in our measures.

2.3 Quantifying Disparities

Scholars from varying fields of education research have developed metrics to quantify and monitor disparities. In special education, a closely-monitored area of concern is whether students of different subpopulations are identified as qualifying for special education services at similar rates. One metric used to monitor this is the composition index [23,24], which is equivalent to the metrics reported in the State of CS report mentioned above and is calculated by dividing the number of students of a particular subgroup who were identified for special education by the total number of students identified. Again, the drawback here is that the metric by itself does not provide any assessment of equity since additional information would be needed to know whether the identification rate of a particular subgroup was proportionate to the percentage that subgroup comprises in the population. Another metric used is the risk index [23], which is computed by dividing the number of students of a particular subgroup identified for special education services by the total number of students of that subgroup in the population. The metric thus represents the percentage of students from a given subgroup that are identified for special education. However, similar to the composition index, the risk index does not provide any evaluation of equity in and of itself as it requires comparing values between subpopulations.

To overcome the limitations of these metrics, special education researchers often use risk ratios [25,26], which are calculated by dividing the risk index for one subgroup by the risk index of another subgroup. The resulting value provides a measure of the extent to which one subgroup is over- or under-identified compared to the other subgroup.

Similar metrics have been used in other fields, such as school discipline [27] and child welfare [14]. In addition to risk ratios, metrics of risk difference have also been used in school discipline research [27]. Rather than dividing the risk index of one group by that of another, risk difference is computed by subtracting one group's risk index from that of another. Like the risk ratio, this metric provides a way to compare groups using a single value. However, because it simply represents the difference between proportions, it is possible for the same value to be obtained for pairs of proportions that differ significantly in size (e.g., .25 - .20 = 05 and .10 - .05 = .05). Thus, in contrast to the risk ratio, the risk difference metric falls short of providing meaningful comparisons across proportions of varying sizes.

3 MEASURING DISPARITIES IN CS ED.

The CS education community stands to benefit from the development and use of improved methods for quantifying disparities. However, to our knowledge, no research has been conducted within the field of CS education that specifically addresses this issue of how best to quantify disparities. To quantify disparities in CS education, we utilized a metric comparable to the risk ratios used in special education and school discipline research. However, in the context of CS education, the uses for such a metric are measures of positive outcomes (e.g., comparing proportions of different subgroups of students who enroll in CS courses) and not indications of something that would be termed a risk. Thus, rather than calling it a risk ratio, we adopted the term, disparity index, used by Shaw et al. [14].

In this section, we introduce the disparity index (DI) as a method for quantifying inequities in CS education in a way that allows for comparisons across different subpopulations of students at the school, district, region, state, or national level. We first explain the data sources and the sample of students used in the study. Next, we describe the disparity index and how it is calculated. We then explain how using the disparity index can yield important insights not gained through other approaches by reporting the results of how we used this metric to assess equity, account for intersectionality, and distinguish between access to and participation in CS education. We have structured the section such that we present the results and discussion together rather than as separate sections.

3.1 Data Sources

The data we used for this study were obtained through the Texas Education Research Center, a data clearinghouse that contains all public education data collected by the state. Our sample includes demographic and course-taking data for all 2017-18 public high school students in Texas (N=1,537,073). We identified high school students as anyone enrolled in 9th to 12th grade. Accordingly, high schools were defined as any school that served one or more grades between 9th and 12th. Access to and participation in CS education in this study is defined as, respectively, attending a school that offers one or more CS courses and enrolling in one or more CS courses when offered at the school. Lastly, we wish to note that in referring to the various subpopulations of students identified in the data, we chose to use the terms as they appeared in the state data we accessed.

3.2 The Disparity Index

As mentioned previously, the disparity index mirrors the risk ratios utilized in other education research fields in that it is a ratio of the proportion of one group over the proportion of another. Exactly what the proportions represent can vary depending on how the index is used. In this study, we calculated two types of disparity indices: one to measure disparities in terms of access to CS education and one to measure disparities in terms of participation or enrollment in CS education. For both types, the disparity index is computed the same way and is defined as the quotient of the rate (or proportion) for the target population over the rate for the comparison group:

$$DI_{targetgroup} = \frac{rate_{targetgroup}}{rate_{comparisongroup}} \quad (1)$$

For example, to calculate the disparity index for female students in terms of participation in CS courses, we would divide the proportion of females who enrolled in a CS course by the proportion of males who took CS:

$$DI_{females} = \frac{rate_{females}}{rate_{males}} \quad (2)$$

The DI provides a quick look at the degree to which the target population is over or underrepresented in terms of access to or participation in CS education relative to the comparison group. A DI of "1" would signify equal representation, whereas a DI less than or greater than 1 indicates underrepresentation or overrepresentation, respectively. The further the value is from 1, the greater the degree of disparity. When considering the degree of disparity, it is important to note that disparities denoting underrepresentation (i.e., DI<1) are on a scale between 0 and 1, whereas disparities representing overrepresentation (i.e., DI>1) are on a scale between 1 and infinity. As a result, disparities of overrepresentation are more intuitive to interpret than those of underrepresentation. For example, a DI of 4 for participation in CS education indicates that the target group is four times more likely to enroll in CS than the comparison group, and a DI of .25 indicates the opposite: the target group is four times less likely to take CS than the comparison group. At first glance, a DI of .25 may not be readily understood to mean "four times less likely," and even less interpretable would be values of, say, .18 or .72. However, understanding that the DI for the target group is simply the inverse of the DI for the comparison group makes the practical interpretation of such values more accessible. If the target group's DI is .18, the comparison group's DI is 1 ÷ .18 = 5.56. Thus, we can interpret the DI of .18 as indicating that the target group is 5.56 less likely than the comparison group. Examples DIs and their inverses are provided in Table 1 for various subpopulations of high school students in Texas.

Table 1: Disparities in CS enrollment for various student subpopulations compared to all other students

	DI	1÷DI
Rural	.84	1.19
Urban-Suburban	1.19	.84
Female	.37	2.72
Male	2.72	.37
Economically disadvantaged	.66	1.52
Special education	.57	1.77
Limited English proficiency	.64	1.57
Immigrant	82	1.22

3.3 Demographics with More than Two Categories

The comparison group used in calculating the disparity index can vary when more than two mutually-exclusive subgroupings exist for the type of demographic being assessed, such as with students' race/ethnicity. For example, when calculating the disparity index for Black students, any other mutually-exclusive race/ethnicity category (e.g., Asian, Hispanic/Latino, White, etc.) can be used as the comparison group. Using more than one comparison group and calculating multiple disparity indices for a particular group can help refine our understanding of the nature of educational inequities for that group. However, it can present a challenge for obtaining an overall picture of the disparity for those students, which can be especially important for tracking inequities over time and as part of large-scale summary reports of educational equity [28]. One solution to this is to compute the disparity index using all other students as the comparison group. This provides one general indicator of disparity for each group and can make it easier to make comparisons across educational systems and measure progress based on longitudinal trends.

Despite the benefits of utilizing one general disparity metric for each subgroup of students, important information can be lost when the metric for the reference group represents an average of multiple subgroups. For example, including all other students as the comparison group when calculating the disparity index for Black students (who tend to be underrepresented in CS), would mean that

Hispanic/Latino students (who also tend to be underrepresented in CS) would comprise part of the comparison group, thus mitigating the resulting disparity index and masking the true disparity.

To overcome this limitation, disparity indices can be calculated by combining racial/ethnic subgroups into over or underrepresented categories to be used as the comparison group. Disparity indices for each underrepresented racial/ethnic subgroup are computed using the combined overrepresented category as the comparison group, and disparity indices for overrepresented subgroups are computed using the combined underrepresented category as the comparison group. Research has shown that Asian and White students are consistently overrepresented in computing education in high school [5] and in college [17,29]. Since the underrepresentation of one group can only be defined in contrast to the overrepresentation of another group, it makes sense to quantify the degree of underrepresentation in CS education for individual racial/ethnic groups by using Asian and White students as the comparison group. Using this method, the DI for Black students becomes .50 and for Hispanic/Latino students it is .57, indicating that the combined likelihood that Asian and White students will take CS are double that of Black students and slightly less than double that of Hispanic/Latino students.

Table 2 provides a side-by-side comparison of disparity indices calculated using these different types of comparison groups. The table thus shows how the choice in the comparison group affects the value of the disparity index. As might be expected, the DIs for individual subgroups varied widely depending on which racial/ethnic category was used as the comparison group.

3.4 Accounting for Intersectionality

When identifying and addressing inequities in education, it is important to take into account the fact that students do not belong to just one social group. In this section, we provide some examples of ways to begin to move beyond the one-size-fits-all approach to assessing differences based on demographics by accounting for the intersections among students' multiple social identities and circumstances. Further examples of accounting for intersectionality are also given in the subsequent section on access and participation.

As a preface to the results we will report, we wish to point out that current methods (including those used here) to quantify such complex constructs fall far short of being able to fully account for the myriad social identities applied to students by themselves or by others. In the context of the current study, this is exemplified by the fact that our ability to account for the intersectionality of students' identities is limited to the nature and structure of the available data. Thus, interpretations of the results should be made always with the understanding that the results only represent a small part of all the social groups and categories that individual students' identify with. Additionally, it is important to note that quantification itself inherently "imposes a very strong meaning system on the information" that it represents [30, p. 36]. The lesson there is that one should be cognizant of the fact that the meaning and implications of the disparities identified between social groups are more complex and go much deeper than our relatively simple quantitative measures can convey.

Notwithstanding these methodological limitations, much can be gained by considering even a few ways in which membership in social groups intersect. Figure 1 visualizes the disparities between several different subgroups of Black and Hispanic/Latino students and their Asian and White peers. Because the subpopulations featured in this chart are all underrepresented in CS compared to Asian and White students, and to make the disparities easier to interpret, we configured the y-axis to represent the inverse of the disparity index for these subgroups. Thus, the values of the y-axis can be interpreted as the number of times less likely to take CS each subgroup is than Asian and White students or, in other words, the likelihood of not enrolling in CS compared to Asian and White students.

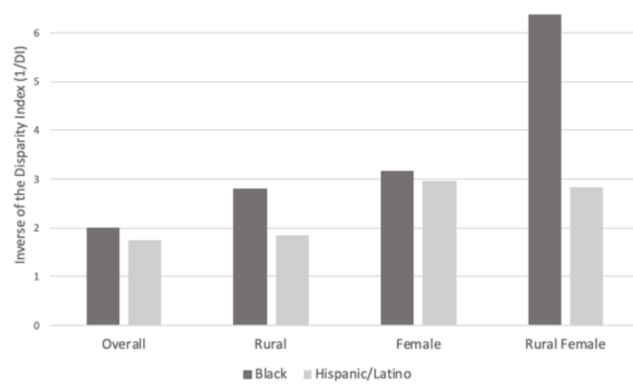

Figure 1: Disparities in CS Enrollment for Black and Hispanic/Latino Students (Compared to Asian and White Students)

These data underscore the importance of accounting for intersectionality in measures of access and participation as they show how disparities can be compounded for students who are members of more than one underrepresented group. This is noted most expressly in comparing the disparities for Black students, Black females, and rural Black females. Black students are two times less likely than Asian and White students to enroll in CS, but Black females are three times less likely and Black females in rural areas are six times less likely to enroll.

3.5 Disentangling Access and Participation

When assessing equity in CS education, measures should distinguish between indicators of access and indicators of participation. In other words, it is important to assess equity in terms of students' access to CS courses as well as students' participation in CS courses. In this section, we describe how the disparity index can be calculated for both types of indicators and offer a few important considerations and guidelines for doing so.

3.5.1 Access to CS Education. Equity in terms of access can be measured by comparing rates at which students attend a school that offers CS courses. For example, research has shown that rural schools tend to be less likely to have a CS program than urban and suburban schools. We calculated the disparity index in terms of access to CS for rural students by dividing the proportion of rural

Table 2: Disparity indices by race/ethnicity based on different types of comparison groups

Target Group (Numerator)	Asian	Black	Hispanic/ Latino	American Indian/ Alaska Native	Native Hawaiian/ Pacific Islander	Two or more races	White	All Others	Asian or White	Black or Hispanic/ Latino
Asian		4.56	3.96	3.62	3.13	2.57	2.92	3.57		4.07
Black	.22		.87	.79	.69	.56	.64	.66	.50	
Hispanic/ Latino	.25	1.15		.91	.79	.65	.74	.66	.57	
American Indian/ Alaska Native	.28	1.26	1.09		.87	.71	.81	.87	.63	1.13
Native Hawaiian/ Pacific Islander	.32	1.45	1.26	1.15		.82	.93	1.00	.72	1.30
Two or more races	.39	1.77	1.54	1.41	1.22		1.13	1.23	.88	1.58
White	.34	1.56	1.36	1.24	1.07	.88		1.12		1.40

students who attended a school that offered one or more CS courses by the proportion of urban and suburban students who attended a school with CS. In 2017-18 in Texas, this resulted in a DI of .79. As the quotient of 1 and .79 is 1.26, we can interpret this to mean that urban-suburban students were 1.26 times more likely than rural students to attend a school that offers CS.

Another way to measure access to CS education could be to use counts of schools rather than counts of students. For example, one could calculate the proportion of schools in rural areas that offer CS and compare this to the proportion of schools in urban-suburban areas that offer CS. A disparity index could then be computed by dividing the proportion of rural schools that offer CS by the proportion of urban-suburban schools that offer CS. It is important to note, however, that each method can produce very different results, which, in turn, have different interpretations. For example, there were 457 urban and suburban high schools that offered CS out of a total of 836 urban and suburban high schools in Texas in 2017-18. For rural areas, there were 425 high schools that offered CS out of a total of 1,115 high schools. Calculating the disparity index for rural schools based on these ratios results in a DI of .70, indicating that rural schools are 1.43 (1 ÷ .70 = 1.43) times less likely to offer CS than urban-suburban schools. Comparing the DI for rural schools (.70) to that for rural students (.79) reveals that the disparity is greater when counting schools than when counting students. The reason for this is that rural schools have many fewer students, on average, than urban and suburban schools. Because of anomalies like this, consideration should be given to which method is used to investigate disparities.

3.5.2 Participation in CS Education. Equity in terms of participation in CS is often assessed by comparing the rates at which different groups of students enroll in CS. However, these measures often do not limit the base population to only those students who attend schools that offer CS. The problem with including the entire population (i.e., including students at schools that do not offer CS) in measures of participation is that it remains unclear whether disparities are due to a lack of access to CS courses or to disproportionate participation in those courses. As an example, consider the AP exam rates that are frequently reported by race/ethnicity. The Google Gallup [31] report noted that less than 15% of all AP CS A test takers in 2014 were Black or Hispanic. Another study [32] reported that in 2015, 3.9% of test takers were Black and 9.2% were Hispanic. Both of these publications report accurate percentages of exam takers who were Black and Hispanic, but it remains unclear from these data the extent to which these low percentages are due to Black and Hispanic students enrolling in AP CS in lower numbers and the extent to which they are due to higher proportions of Black and Hispanic students attending schools where AP CS is not even offered.

To overcome this limitation, we argue that measures of participation in CS education should be constructed so as to distinguish from and be mutually exclusive of measures of access to CS education wherever possible. This can easily be done by limiting the base population to include only students who attend schools that offer CS.

3.6 Access, Participation, and Intersectionality

Computing and comparing metrics of access to CS education alongside metrics of participation in CS education can be a powerful tool for assessing inequities. To illustrate this, we created scatter plots that show the disparity indices of both access to and participation in CS education for various subpopulations of students (Figures 2 and 3). As noted previously, disparity indices that represent underrepresentation will have values less than 1 with the possible range of values being between 0 and 1. Conversely, disparity indices representing overrepresentation will have values greater than 1 and be on a scale that ranges from 1 to infinity. This presents a problem for plotting values for both under and overrepresented groups on the same chart. To get around this problem, we converted the values to logarithmic scale by computing the natural log of each value. This makes practical interpretation of the individual scale values infeasible but it allows for all values to be plotted on the same chart without changing the relative distance between values.

Figure 2 displays the access and participation disparity indices for various racial/ethnic subpopulations. All disparity indices plotted on this figure were computed using the access and participation rates of either of two reference groups in the denominator. The y-axis represents disparities in terms of participation in CS. Values falling above the midline (the zero point) are indicative of subgroups that are overrepresented in CS courses compared to all other students. Only two subgroups included in the chart fell well above the midline: male students and urban-suburban male students. Values landing below the midline represent groups that are underrepresented in terms of participation in CS. Most groups fall into this category with female subgroups showing the largest disparities. The x-axis represents disparities in terms of access to CS education. Values falling to the right of the midline (the zero point) mark subgroups that are overrepresented in terms of access to CS education whereas values to the left of the midline are indicative of groups underrepresented in terms of access to CS.As noted previously, Asian and White students have consistently been shown to be overrepresented in CS education compared to the rest of the population whereas Black and Hispanic/Latino students have been shown to be underrepresented. We found the same to be true in the data we examined. For those reasons, we chose to use Asian and White students as the comparison group for all non-Asian/non-White subpopulations, and to use Black and Hispanic/Latino students as the comparison group for Asian and White subpopulations.

The majority of subgroups fell into the underrepresented regions in terms of either access or participation or both. Most of the variation in terms of access to CS education fell along rural and urban-suburban lines. The only rural subpopulation to be overrepresented in terms of access was rural Asian students.

Interestingly, Hispanic/Latino students were also less likely to have access to CS courses than non-Hispanic/Latino students but Black students were equally as likely as non-Black students to attend a school that offered CS. As was noted previously in reference to Figure 1, disparities in terms of participation in CS were compounded for Black females in rural areas beyond the disparities noted for Black females and Black students overall. As the data in Figure 2 show, we now see that the same is true for disparities in access for rural Black females. This again highlights the usefulness in accounting for the intersectionality using the available demographic data in order to identify how disparities may differ for different subpopulations.

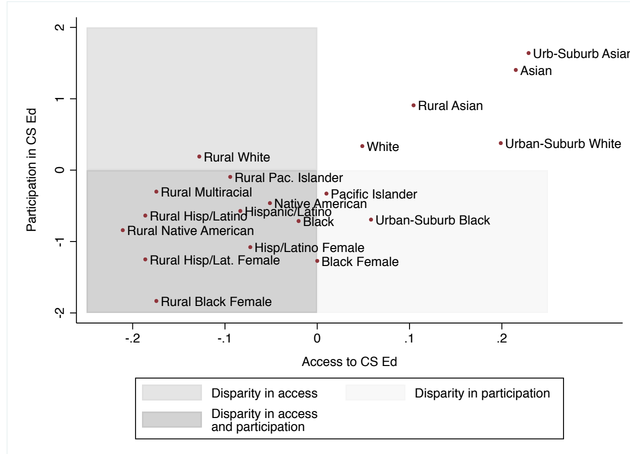

Figure 2: Disparity Indices (Logarithmic Scale) for Various Racial/Ethnic Subpopulations of High School Students in Texas 2017-18

4 CONCLUSION AND IMPLICATIONS

Understanding how inequities in computing education are evidenced in both access and participation allows researchers and practitioners to develop strategies for addressing these disparities that specifically target the underlying barriers and challenges rather than applying one-size-fits-all approaches. For example, in this study, Black females and Black students overall in Texas had very similar rates of access to CS courses but notable differences in terms of participation in CS courses. Such information can be helpful in developing strategies to address inequities such as targeting recruitment strategies specifically to the needs and interests of black female students since access alone is not sufficient to eliminate these disparities.

In addition, the difference in disparities among Black and Hispanic/Latino students overall and Black and Hispanic/Latino students in rural areas is important to note. The fact that Black students and Hispanic/Latino students had similar disparities in participation when considering the overall population of students in schools that offered CS but different disparities when limiting the data to rural areas signifies that there is an important distinction between what it means to be a rural student for Black students vs what it means to be a rural student for Hispanic/Latino students. This speaks to the importance of considering students' intersectionality in creating and utilizing metrics to assess equity.

A limitation of this study is that it only partially, perhaps even minimally, accounts for the intersectionality that exists in students' social identities. For example, we showed how disparities were compounded for black females and then again for rural black females, but those categories still only represent a part of the complete identities of the students identified in those subpopulations. Future research would do well to expound on the demographic intersections examined here to advance our collective understanding in this area.

This study demonstrates the importance of examining issues of intersectionality in both access to and participation in computing education in order to more fully understand the complexities of educational equity. The additional information obtained by accounting for these facets of equity research can be used to craft interventions that address the specific challenges evidenced by the data. To that end, we encourage CS educators and researchers to 1) utilize these methods and metrics to disentangle and illuminate the various factors that may be contributing to disparate outcomes in computing for students across a wide range of backgrounds and identities, and 2) explore how the information obtained can be used to inform efforts to create learning environments that are more inclusive of all students.

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