16 Equity and Diversity

Colleen M. Lewis, Niral Shah, and Katrina Falkner

1 Introduction

It is frequently observed that some groups are underrepresented in computing education and the computing profession. While these patterns of underrepresentation vary by country, in many Western countries, computing is dominated by white and Asian men. For example, in the USA, people who identify as black, Latinx, Native American, or Hawaiian and/or women are not participating at rates comparable to their portion within the US population (National Science Foundation, National Center for Science and Engineering Statistics, 2017). Perhaps surprisingly, in this chapter, we will not summarize the current state of underrepresentation. These patterns of underrepresentation are not unique to computing and are general patterns that can be seen across most science, technology, engineering, and mathematics (STEM) fields. These patterns can also be seen in non-STEM disciplines and are typically consistent with other systems of inequity (e.g., sexism and racism). Documentation of patterns of underrepresentation may provide motivation for action, but does not point to the necessary actions. We argue that understanding the ways in which systems of inequity produce dominant and marginalized groups is essential to understanding and addressing current patterns of underrepresentation and inequity.

1.1 Goals and Structure of the Chapter

In this chapter, we hope to provide readers with resources for understanding the roots of underrepresentation and how these can play out in computing classrooms. Throughout the chapter, we explore the relevance of narratives about computing and computer scientists for issues of equity and diversity. We begin by developing a shared set of terminology as it relates to equity research in computing education (CEd; Section 1.2). This includes exploring common arguments for why addressing patterns of underrepresentation in computing is a pressing concern. We next introduce these narratives, their connections to historical patterns of marginalization and injustice, and our use of “narratives” as opposed to the more common term “stereotypes” (Section 1.3). We then introduce research related to unconscious or implicit bias in order to identify the ways in which these narratives about computing and computer scientists

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can produce harm and the patterns of underrepresentation that are frequently observed (Section 1.4).

Instead of providing a decontextualized review of the remaining literature, we ground our review within four hypothetical scenarios that we call vignettes (Section 2). These vignettes allow us to show how the research helps us understand particular patterns and interactions within computing classrooms. These vignettes also concretely illustrate the relevance of particular interventions used to promote diversity in computing. The chapter closes by expanding this focus and identifies open questions (Section 3). These open questions provide pointers to relevant literatures outside the scope of the chapter.

1.2 An Overview of Equity Terminology and Rationales for Action

Terms like "equity," "diversity," and "access" have proliferated in computing education to describe and conceptualize issues related to marginalized groups. Indeed, these terms figure prominently in many of the foundational documents in computer science (CS) education (e.g., the K–12 Computer Science Framework, 2016). In using these terms throughout this chapter, we want to provide a common understanding of what these terms mean. Further, we note that there has been a tendency to conflate these terms in problematic ways. For those reasons, we begin by briefly discussing conceptual distinctions between them, as well as their relative affordances and limitations.

"Equity" has been an umbrella term used throughout much of the CEd research (CEdR) literature, which has been conceptualized at multiple grain sizes corresponding to multiple organizing concepts. In everyday use, equity and equality are sometimes used interchangeably, but for our purposes, the differences are important. Equality refers to the state where everyone has or is allocated the same things in the same degree, whereas equity typically refers to having access to what is needed. Equality can be a waypoint toward equity, but they are not the same thing (Reinholz & Shah, 2018). There are situations where everyone might need the same thing in the same degree, in which case equality would also be equitable. In general, though, equity, and not equality, defines fair and just learning opportunities.[1] A limitation of the term is that achieving equity relies on the difficult task of knowing what students need.

Within the umbrella of equity, an organizing concept is "diversity," which refers to which groups are and are not represented or included in various spaces and practices. In computing and CEd, studies have focused on diversity in computing classes and majors (Google Inc. & Gallup Inc., 2016), in Advanced Placement test-taking (College Board, 2017), and the workforce (Information

1 The comment "women's groups are unfair" may be an example of conflating equity and equality. If a "women in computing" group is only open to women, then this is not equal for people of all genders. That is, what people are provided is not the same. However, a women's group may be important to help counteract some of the narratives about the inferiority of women as discussed in this chapter. Ultimately, equity and fairness do not necessitate equality.

is Beautiful, 2016), to name a few. The impetus for diversity in computing is manifold.

First, there is a moral concern that the computing community reflect society writ large, particularly with respect to race, gender, dis/ability, sexuality, and other social markers. Rather than be restricted to certain groups or an elite few, many in the field espouse the democratic view that computing be widely available. This perspective is reflected in numerous initiatives advocating "CS for all" (Ladner & Israel, 2016).

Second, some link diversity to the size of the workforce, suggesting that greater inclusion is needed to fill gaps in the computing labor force (National Center for Women & Information Technology, 2017). Expanding diversity in the workforce would require increased participation by people from groups that are currently underrepresented in computing, which could have the result of increasing the total number of workers.[2] Third, there is a related pragmatic and economic argument that diversity in product design teams will lead to better products. One explanation for this benefit is that diverse teams have been shown to produce better results (Hunt et al., 2018). A second explanation for this benefit is that the team may choose to make products that are accessible to a greater portion of consumers in the marketplace (K–12 Computer Science Framework, 2016, p. 29). However, this second explanation may require decision-makers within the organization to see more accessible products as consistent with their financial incentives or moral values, which does not directly relate to the social identities of the product design or engineering team.

Within the umbrella of "equity," another organizing concept is "access," which acknowledges that representation and performance in computing are closely related to students' access to the resources needed for participation in computing. This way of thinking about access also relates to the prevailing metaphor of "participation": opening access to these kinds of structural resources is viewed as a critical lever toward broadening participation to include students from marginalized groups[3] in the computing "pipeline." In computing, studies have attended to the number of schools that offer computing courses (Google Inc. & Gallup Inc., 2015), racial and class disparities in the communities where those computing courses are offered (Margolis et al., 2012), and disparities in access to qualified computing teachers and the physical resources needed to study computing (Google Inc. & Gallup Inc., 2015; Margolis et al., 2008). Importantly, the focus on access shifts attention from performance gaps to *opportunity* gaps between dominant and marginalized groups (Milner, 2012). By measuring disparities in how access has been distributed in society, researchers

2 However, when relating diversity to the expansion of the workforce, the term "diverse" is sometimes used to label individual people, as in "a diverse computer scientist." This example does not use diverse to describe variation within a group of people. This non-standard usage may instead represent avoidance of discussing social markers such as race, but these discussions are likely necessary for increasing diversity.

3 In the USA, people who identify as African American, black, and/or Latinx are typically referred to as members of marginalized groups (Walton & Cohen, 2011), but many social markers can lead to marginalization.

reduce opportunities for people to interpret performance or participation gaps as innate differences in potential, intelligence, or interest.

In addition to structural resources, "access" has also been conceptualized in terms of the content and organization of the learning environment itself. As Margolis et al. (2012) note, "broadening participation goes beyond issues of access to computer science (CS) learning; we also must transform CS classroom culture and teaching" (p. 71). To that end, studies have investigated the affordances of building on students' cultural funds of knowledge[4] (González et al., 2006) and situating computing ideas in real-world problem-solving (Goode, 2008; Kafai et al., 2014; Margolis & Fisher, 2003; Margolis et al., 2014). These pedagogical efforts seek to move beyond traditional lecture formats and narrow views on computing content to make deeper connections to students' lives and backgrounds. Further, there has been research examining equity and inequity in student participation patterns across various classroom interactional contexts, such as pair programming (Lewis & Shah, 2015; Shah & Lewis, 2018).

Finally, a term that is receiving increasing attention in this part of the field is "social justice," in which students use computing for the purpose of addressing injustice in their local communities and in society writ large (Bobb, 2016; Toyama, 2015; Vakil, 2014). This perspective challenges widely held assumptions about the very purpose of CEd. Rather than simply enrolling more students of color in computing majors or hiring more women software engineers, computing is conceptualized as a "discipline in service of society, its people, and their needs" (K–12 Computer Science Framework, 2016, p. 26). Importantly, this view acknowledges that CEd is situated within a sociopolitical context. This necessitates a more expansive view of what we mean by "equity" in computing, from considering equity within CEd to considering equity across society.

In summary, various terms organize field-wide discourse about equity and marginalization. A key point, though, is that none of these terms by themselves are adequate – each has its affordances and limitations. In our view, this seems entirely reasonable, as "equity" is a complex, multifaceted idea that cannot and should not be reduced to a single perspective. While a comprehensive analysis is beyond the scope of this chapter, tensions between these various ways of conceptualizing equity issues in computing set the stage for future research in this area. We return to this at the end of the chapter in our discussion of open questions (Section 3). Next, we review narratives about computing and computer scientists and explain our use of narratives instead of the related term "stereotypes." We highlight narratives and stereotypes separately from the terms described above because of the importance of narratives in understanding historical patterns of marginalization and injustice.

4 Moll et al. (2006) define funds of knowledge as "historically accumulated and culturally developed bodies of knowledge and skills essential for household or individual functioning and well-being (Greenberg, 1989; Tapia, 1991; Vélez-Ibáñez, 1988)" (pp. 72–73).

1.3 Narratives about Computing and Computer Scientists

Negative stereotypes of computer scientists are pervasive (Ensmenger, 2010). We argue that the systems of inequity appear to rely on stereotypes about computing and computer scientists. However, instead of referring to these as stereotypes, we will use the term "narrative." We see the terms "stereotypes" and "narratives" as connected, but conceptually distinct. The term "narrative" captures the notion that beliefs about computing and computer scientists are communicated by and between people and therefore can and do change. The stories that people tell about computing and computer scientists form the basis for what we think about the field and its practitioners. By changing the stories (i.e., the narratives), we can (and should) change our thoughts about computing and computer scientists.

A prevailing narrative is that computer scientists are socially inept, non-hygienic, white men (Ensmenger, 2010). These exclusive narratives about computer scientists can discourage participation if they are interpreted as requirements of the field or even just present an unappealing view of the social interactions that a career in computing might involve (Lewis et al., 2016).

In addition to narratives like these about who computer scientists are and how they behave, there are also narratives about the nature of computing ability. For example, there are prevailing beliefs that it requires a "geek gene" (Ensmenger, 2012; Lewis et al., 2011). This connects to other narratives about intelligence – who has it and who doesn't. In particular, there has been a historical pattern of claims that some people have inferior intellects (Kendi, 2016). While reports of biological differences among races continue today (Reich, 2018), this work has long been critiqued as "scientific racism" (Fairchild, 1991). People have attempted to use science to explain why people of African descent are intellectually inferior (Bobo et al., 2012; Kendi, 2016). However, these claims are false and have no empirical basis.

Stepping back, we want to consider some of the staying power of these narratives. If these narratives about innate differences between groups are false, what supports their continued existence? This can be explained by a few things. First and foremost, the narratives are hierarchical and benefit some people. For example, the narrative that black people are intellectually inferior implies that non-black people are intellectually superior (Kendi, 2016). In this chapter, we will identify some of the ways in which these hierarchical narratives serve to affect behavior and outcomes that ultimately benefit or harm particular individuals and groups.

1.4 Unconscious Bias

As mentioned above, narratives can be discouraging to individuals because they may present a narrow view of who can do computing or the values and characteristics of the community that might be required in order to join. However, this individual-focused explanation of how these narratives discourage participation is only part of the story. Most obviously, these narratives can cause harm through explicit, conscious bias referred to as "prejudice" (Amodio, 2014). That is not the primary focus here because it appears to be more easily identified (although no more easily addressed). Instead, we focus on the less overt forms of bias that can cause disadvantage and marginalization and are fueled by these narratives – "implicit bias" or "unconscious bias" (Greenwald & Banaji, 1995).

Unconscious bias influences split-second decisions, is fueled by narratives, and causes harm to those who are negatively stereotyped. The evidence of these biases primarily comes from what are referred to as "résumé studies" (Steinpreis et al., 1999). In this line of research, two copies of the same résumé are made and sent to people who might hire someone in the same field as the résumé. One group of people receive a copy of the résumé with one name on it. Others receive a copy of the résumé with a different name on it. Researchers modify the names to see if names that are associated with negative stereotypes about intelligence receive less positive responses. In Moss-Racusin et al.'s (2012) study on the influence of gender on application assessment, they found that both male and female science faculty rated male applications significantly higher than female applicants, selecting a higher starting salary and professional development support. Bertrand and Mullainathan (2004) used stereotypically white and African American names, and applications were found to be more likely to result in an interview request if associated with a stereotypically white name. Pager (2003) explored this in a follow-up study incorporating multiple participants interviewing for positions with a number of set CVs and identical interview training; they found that African American candidates with no criminal record received a callback at the rate of white candidates with a criminal record.

Another stunning example of unconscious bias comes from studies of hiring (Uhlmann & Cohen, 2005). Research participants were asked to evaluate applicants for a police chief position. One of the provided applicants had significant practical experience while the other had significant academic experience. The researchers found that whichever résumé they put a man's name on (with a woman's name on the other résumé), the participants would offer reasoned arguments about the importance of particular aspects of the male applicant's credentials. In the case where the man's name appeared on the résumé with practical experience, they argued for the importance of practical experience. In the case where the man's name appeared on the résumé with academic experience, they argued for the importance of academic experience. This shows that even when decisions involve a sound rationale, that rationale may be unconsciously shaped by bias.

While these examples may be a bit removed from the context of computing education, letters of recommendation may also demonstrate implicit bias. Studies show that authors tend to use more communal and supportive language when writing letters of recommendation for female candidates and more decisive and direct language when writing for male candidates (Madera et al., 2009; Trix & Psenka, 2003). This influence hits in multiple ways – not only in the way that recommendations are made, but then also in how they are perceived (see Barker, 2010, for a review and recommendations for avoiding such bias).

As additional evidence of bias, studies have found that both parents and teachers tend to overestimate boys' abilities in mathematics and science areas (Lindberg et al., 2010). Research has demonstrated that teachers treat boys and girls differently in their development of mathematical skills, with boys encouraged to pursue independent problem-solving processes, while girls are encouraged to follow fixed, algorithmic approaches (Hyde & Jaffee, 1998). Girls are less likely to be encouraged into CS roles by parents and teachers, with boys being more likely to be told explicitly that they could be good at CS (Google Inc. & Gallup Inc., 2017).

A natural question in the research above is whether the research participants in these examples were demonstrating sexism or racism. The answer depends upon the definitions of these terms. Certainly, the research suggests that people, regardless of their identities, have biases consistent with these cultural narratives that may unconsciously shape their words and behavior. When biases about race are embedded within policies and practices within institutions, it is referred to as structural racism,[5] even though it does not imply racist intent.

1.5 Aggregate Harm from Unconscious Bias

While some of these studies described above may seem to lead to small differences, even such small differences can have enormous aggregate impact. In particular, as researchers and educators, we are interested in considering the aggregate impact of unconscious bias and the ways in which it is embedded within policies and practices within institutions (Smith, 2015, p. 35). To consider the potential for aggregate harm, we remind the reader about emergent phenomena in which small behaviors can lead to macroscopic, observable patterns. Similarly, a small magnitude of bias could lead to macroscopic patterns of discrimination, marginalization, or underrepresentation.

Martell et al. (1996) created a simulation of bias against women in a company that was originally populated at every level of the company by 50 percent women and 50 percent men. To simulate bias, men were rated each year with scores of 1–100 and women were rated each year with scores of 0–99. They simulated multiple years, assuming yearly attrition and yearly promotions based upon ratings. The simulation showed a much larger pattern of underrepresentation of women at senior levels (only 35 percent at the top level). This simulation helps us connect our understanding of bias to the larger patterns of emergent phenomena; even small amounts of bias can lead to a substantial aggregate impact.

Additionally, research has also shown that students' perceptions of their abilities can also be impacted by bias, with teachers' perceptions of ability predicting students' own assessments (Keller, 2001; Tiedemann, 2000). This can form a

5 Smith (2015) states, "Institutionalized isms are standards, policies, and practices that are embedded in the institution, that have a disparate impact on particular groups, and that are not essential to fulfill the institution's mission" (p. 35).

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negative cycle of ability perception, leading students to make critical decisions on capability, career goals, and study directions based on information that does not truly reflect their capability or potential.

1.6 Call to Action

This chapter seeks to help connect patterns of underrepresentation to these larger cultural narratives and systems of oppression such as sexism and racism. However, in doing so, it may appear that these problems are too large. These problems are indeed interconnected with these larger systems of oppression, and these problems are unlikely to be completely addressed without dismantling these larger systems. However, just as small amounts of bias can lead to an aggregate effect, so too can work to counteract these narratives and bias lead to an aggregate effect. We hope that our readers can see the historical roots of the problems while also seeing the imperative to act within their sphere of influence to make change and work toward justice.

For example, it is important to consider times when we are making decisions that are subjective because these subjective decisions are likely to be affected by bias. While these processes of bias are unconscious, it requires conscious effort to counteract them (Fiarman, 2016). If grading sometimes requires giving students "the benefit of the doubt," this may unconsciously be unevenly applied to student work (Malouff & Thorsteinsson, 2016). Educators may mitigate this by grading student work anonymously and using rubrics when possible. Research shows that being more aware of the biases that we have can help us reduce their impact on our decision-making (Morewedge et al., 2015). Even in our local decisions about grading we can contribute to addressing these much larger problems.

2 Vignettes

The following vignettes present hypothetical scenarios that we expect to resonate with the concerns and experiences of educators. We expect that this computing classroom-focused perspective also aligns with the interests of CEd researchers. Within the analysis of each of the vignettes we hope to provide helpful references to relevant research from CEd and beyond. Across the four vignettes, we draw on unconscious bias and the underlying narratives that fuel this bias, as described above (Sections 1.4 and 1.3, respectively). Additionally, we hope to use this research to discredit interpretations of the vignettes that simply apply narrow narratives about computing and computer scientists. Our discussion of each vignette ends with a description of relevant interventions.

2.1 Ways Structural Barriers and Stereotype Threat Shape Performance

As you are reviewing grades at the end of the semester, you notice that the grades of the only two black women in your class, Nia and Kiara, were in the bottom quartile.

2.1.1 Vignette Analysis

We expect that a common interpretation is that those students who do poorly in the course lack an innate ability to learn computing. There is no evidence that there exists an innate ability for computing (Patitsas et al., 2016; Robins, 2010), and a belief in innate ability can lead students to pursue unproductive learning strategies (Dweck, 2008). To analyze this vignette, we will consider two bodies of literature related to structural barriers to computing and stereotype threat.

This analysis still takes into account the identities of Nia and Kiara, but does not rely on the false narratives described in Section 1.3 that women and black people are generally less capable of success in computing. These are false interpretations. Black students *are* competent and as academically brilliant as any other students (Leonard & Martin, 2013). Although this might seem an obvious statement, we feel it is important to state this clearly and unequivocally, particularly in light of long-standing racist beliefs about black people as intellectually deficient (Bobo et al., 2012). These false beliefs persist in the background, even though people might not explicitly vocalize them as often as before.

A first question you might ask is whether Nia and Kiara have had similar opportunities to learn computing as their peers. Differential access can have consequential implications for performance (Lewis et al., 2012). Additionally, research shows previous experience is often conflated with potential (Barker et al., 2002). In the USA, unequal access to computing instruction for black and Latinx students and women has been well documented (College Board, 2017; Google Inc. & Gallup Inc., 2015). In the book *Stuck in the Shallow End: Education, Race, and Computing*, Margolis et al. (2008) described the structures that prevent students of color from having access to a rich computing curriculum. This work by Margolis et al. contributes to the body of work regarding our understanding of structural barriers to accessing advanced coursework for students of color (Mulkey et al., 2005). These structural barriers that disadvantage students of color are typically referred to as structural racism or institutionalized racism.

If Nia and Kiara have had fewer opportunities to learn computing, these broad patterns of structural racism may be a central explanation. However, it is important to remember that descriptions of these broad patterns do not mean that they will apply uniformly to students from a particular group. We should not assume simply based upon their race that Nia and Kiara have had fewer opportunities to learn computing.

Compounding racial disparities in access to CS instruction, women are less likely to have access to CS instruction (College Board, 2017; Google Inc. & Gallup Inc., 2015). While we can connect racial disparities in access to patterns of segregation (Orfield & Eaton, 1996) and structural racism, gender disparities require additional explanation because gender-segregated schooling is much less common. Unconscious bias (Section 1.4) can also explain why women would be less likely to be encouraged by adults to participate in CS learning opportunities. In a US-based survey of 7th through 12th grade students, boys were more likely than girls to be told they would be good at CS by a teacher (39 vs. 26 percent) or a parent (46 vs. 27 percent; Google Inc. & Gallup Inc., 2017). Unconscious bias can also help explain why women might be less likely to choose to participate in CS learning. For students with identities that do not align with current narratives of computer scientists, this fact may lead to them perceiving a lack of fit with computing and depress their interest (Lewis et al., 2016). We know that children start to form gendered views of careers and behaviors at an early age (Miller et al., 2018) and that messages from their community, and specifically key role models, can have a significant impact on the decisions that they make regarding their intended careers and study directions (Google Inc., 2014).

As black women, Nia and Kiara may be less likely to be encouraged to pursue computing because their race and gender do not match the narratives about computer scientists. Research has documented the barriers faced by women of color as a "double bind" (Malcom et al., 1976; Ong, 2011; Ong et al., 2011; Scott & Martin, 2014; Williams et al., 2014). The double bind captures ways in which gender and race contribute and interact to shape the experiences of women of color.

Psychology research has demonstrated evidence of a pattern referred to as "stereotype threat" (Steele, 2010; Steele & Aronson, 1995). This research argues that negative stereotypes may influence our behavior in ways that lead to behavior more consistent with the stereotype (Steele, 2010; Steele & Aronson, 1995). For example, Shih et al. (1999) investigated the impact of the narratives that women are bad at math and that Asian students are good at math. When a group of Asian women were given a math test and reminded of their gender, their performance was lower. When another group of Asian women were reminded of their race, but not their gender, their performance was higher. Stereotype threat has been demonstrated across domains, with some evidence from computing (Kumar, 2012). There is debate among psychologists regarding the mechanism that produces this depression of performance. Schmader et al. (2008) argue that stereotype threat, through multiple mechanisms, consumes students' executive functioning resources. False narratives about the inferior intellectual potential of black people and women create an environment where stereotype threat may take place. This helps us to understand the surprising performance of Nia and Kiara.

2.1.2 Recommendations

Based upon differential patterns of access, it is important to ask: Can students without secondary school experience with computing be successful in these classrooms and programs of study? The most likely place to look for problems is in your institutions' introductory computing course. Given that students come with varied prior experience in computing, it is important to consider what paths through the institution are privileged. For example, at Harvey Mudd College, students are given the option of three different levels of introductory course (Alvarado et al., 2012). There is one course for students with no prior computing exposure. There is a second course designed for students with some prior computing exposure. Because of their prior exposure, it is likely less effortful for these students to develop fluency with the material. To avoid simply reinforcing initial differences in computing experience, this second course covers CS topics that are unlikely to confer an advantage before students reach upper-division CS courses. That is, the goal is to level the playing field between students who start the program with little or no prior experience. There is a third course for students with a lot of prior computing experience. These students take a single course that covers the content of the first two CS courses. Harvey Mudd College's practice of stratifying the introductory course can be seen as contributing to the high percentage of CS majors who identify as women (Alvarado et al., 2012).

A second recommendation is to attempt to avoid stereotype threat. Stereotype threat appears to be mitigated if students are told that the test does not exhibit any bias between groups or if students are not reminded of the stereotyped dimension of their identity (Steele & Aronson, 1995). Additionally, research has found that it can be helpful to communicate to students that tests are an opportunity to provide feedback about their learning, but are not a way to evaluate their potential (Cohen et al., 1999). Additionally, as discussed above, differential participation sometimes results from differential encouragement. Therefore, it can be helpful to provide explicit encouragement.

In addition to strategies specific to removing structural barriers and reducing stereotype threat, "transparent teaching" (Winkelmes et al., 2016) and "active learning" (Freeman et al., 2014) have been shown to have a differential benefit for students of color and other groups. Winkelmes et al. (2016) argue for making assignments "transparent" by stating explicitly what you want students to learn, what the students should do to accomplish the goals of the assignment, and how you will grade students. They found that when faculty made two of their assignments more "transparent," students' self-report of their academic confidence, sense of belonging, and "mastery of skills that employers value" were higher ($p < 0.05$). The effect sizes were higher for students who are the first in their family to attend college, low-income students, and non-white students.

Another class of strategies is referred to as "active learning," which can include a range of pedagogical strategies that seek to encourage students to engage with the content as they are learning. Active learning is sometimes defined as requiring students to do more than listen to a lecture (Freeman et al., 2014). While active learning describes a range of pedagogical strategies, this more-than-lecture set of approaches has been effective at reducing the rates at which students receive a grade of D or F or withdraw from the course (beyond any early course attrition). In a meta-review of 225 studies of STEM classrooms, Freeman et al. (2014) found that students in lecture-only sections were 1.5 times more likely to fail and had lower exam scores (6 percent lower or 0.64 standard deviations). Similarly, Treisman (1992) introduced a structured problem-solving session to create opportunities for collaboration and the development of social connections among black and Latinx students in calculus classes at the University of California, Berkeley. This form of active learning was so effective that it has been replicated across many institutions with positive results in calculus (Moreno & Muller, 1999) and computing (Chinn et al., 2007).

Active learning or other pedagogical improvements may have differential benefits for students with less prior access to computing instruction. Because of racial and gendered disparities in access to computing instruction, more effective pedagogy may tend to be more beneficial for women and students of color of all genders. While the aggregate result of active learning is positive, this obscures variation in students' experiences. It may be necessary to respond to unintended consequences of these interventions even if the research suggests that positive results are likely.

2.2 Ways Environmental Cues Shape Belonging and Identity

Your advanced computing class for computing majors is racially diverse, but most of the students in the class are white or Asian – only three of your students identify as black: Malik, Jaylisha, and Christopher. During class discussions, nearly all of your students participate by asking questions or sharing their ideas. However, Malik only contributes to class discussions occasionally, and Jaylisha and Christopher have not spoken at all in class. This bothers you because you feel committed to all of your students' learning.

2.2.1 Vignette Analysis

One common interpretation of this scenario is that black students are inherently less competent than students of other racial backgrounds and that they might avoid participating in class discussions to hide that incompetence. As described in Section 2.1.1, this is false and relies only on false narratives about black students for support.

A second common interpretation is that black students might be less interested in computing, such that their apathy toward the subject causes them to participate less in class. This is also false. Research shows that black students actually have higher rates of interest in CS fields relative to their peers of other racial backgrounds (Wang et al., 2017). Further, if Malik, Jaylisha, and Christopher were not interested in computing, then they would not have enrolled in the class or remained in the major. Their interest in computing, as well as their potential to excel in computing, should be taken as given.

Finally, a third interpretation of this scenario is that all three of these students participated less because they just happened to be "more shy" or more quiet than their classmates. Certainly, this is plausible – students will vary in terms of their extroversion and willingness to participate in public. However, it is important that educators do not focus on students' personalities to the point that the potential impact of social forces like racism or sexism are minimized or dismissed altogether. Further, even if Malik, Jaylisha, and Christopher all just happened to be more reticent, it is still incumbent on educators to find ways to support them to make their voices heard in class discussions.

First and foremost, it is important to consider student participation in relation to the *opportunities* to participate being made available to students. That is, teachers must consider the extent to which they make participation opportunities accessible to all of their students, especially those from historically marginalized groups. Were Malik, Jaylisha, and Christopher being called on to participate as frequently as other students? What criteria were used to select students for participation? Were only the fastest students to raise their hands invited to participate, or perhaps only those that volunteered at all? Teachers have tremendous discretion over which students do and do not participate in class discussions, and despite one's best intentions, implicit biases can influence who teachers do and do not call on. In fact, research shows that women and non-Asian students of color tend to be both called on less and asked to perform less cognitively demanding tasks when called on (McAfee, 2014; Sadker et al., 2009).

It is also potentially significant that Malik, Jaylisha, and Christopher are the only black students in the entire class. Students in this position can feel tremendous pressure from being "spotlit," as if they are constantly being scrutinized and made to represent their entire race (Andrews, 2012). Do they trust that their ideas will be valued and taken up by their peers and teacher? Understandably, the absence of trust might short-circuit student participation. Additionally, imposter syndrome,[6] where an individual questions their belonging and abilities despite evidence to the contrary, can lead to decreased participation.

Over the past two decades, studies have shown that learning and identity are intertwined (Lave & Wenger, 1991; Nasir & Cooks, 2009; Wenger, 1998; Wortham, 2006). As people learn to do something, they begin to see themselves (and potentially are seen by others) as a *doer* of that thing. Conversely, coming to identify more with a given activity also increases the likelihood of productive engagement in the learning process. Do they see themselves as emergent computer scientists? What kinds of messages along these lines might they be receiving – either explicitly or implicitly – from both their classmates and you?

Whether a student comes to feel they belong and builds a robust identity as a learner of computing depends, in part, on how the computing classroom is structured. Using ethnographic methods, Barker et al. (2002) found that the computing learning environments they studied were often impersonal, isolating, and competitive in ways that fostered defensive classroom climates. Researchers have even found that the physical artifacts and layout of a computing classroom can diminish women's sense of belonging in the field (Cheryan et al., 2009).

6 Imposter syndrome was originally identified as "imposter phenomenon" (Clance & Imes, 1978), but is colloquially referred to as imposter syndrome.

2.2.2 Recommendations

A simple but powerful action that computing instructors can take is to systematically track the participation opportunities they are making available to students from marginalized groups. Instructors can reflect on the extent to which they are actively soliciting these students' participation. In addition to traditional peer observation, tools exist to support instructors in identifying subtle inequities in how participation opportunities are distributed by race, gender, and other social markers (see Reinholz & Shah, 2018). If inequities do exist, then an instructor can think strategically about implementing specific teaching practices to include marginalized students in class discussions. For example, teachers can call on students in a random order so that all students have an equal chance to participate (Shah et al., 2013). We can also try to address more directly students' sense of belonging in our classrooms through encouragement. Additionally, instructors can examine the types of examples we include (e.g., video games) to push back against stereotypical influences that may have impacted our curriculum and our classroom environments.

2.3 Ways Biased Statements Cause Harm

Midterm grades have been posted and students are discussing their scores. It turns out that Marcos, a Latinx student, got the highest grade in the class. John, a white classmate, finds out and tells Marcos, "Nice job, Marcos! You must have that Asian gene!" You overhear this and aren't sure if you should say something or what you should do.

2.3.1 Vignette Analysis

Instructors that do not recognize the fallacy of these cultural narratives might perceive John's comment to Marcos as harmless. Noticing a disproportionately higher enrollment by Asian students in computing at their institution, they might take John's statement as grounded in some degree of truth – that Asians really are naturally better at computing. Alternatively, they might consider it an innocent joke. Indeed, on a superficial level, the statement seems like a compliment to Asians. In our view, it would be a problematic for a variety of reasons.

In the USA, there is a racial narrative that Asian people are inherently superior in STEM fields, such as math, engineering, and computing. Not only do cultural representations of Asians as "technologically savvy" saturate US media (Paek & Shah, 2003), but there is also evidence that students are aware of such racial narratives (Shah, 2017) and even endorse them as they get older (Cvencek et al., 2015). Importantly, though, racial narratives about Asians being genetically predisposed for technology-related fields like computing are false. No empirical evidence exists to support the notion that some racial groups are better than others at computing. Further, such narratives assume that racial categories are somehow "real," as opposed to sociopolitical constructions intended to produce social hierarchies (Omi & Winant, 2015). Another problematic aspect of the comment is that it reflects the widespread narrative that performance in computing depends on an innate ability for the discipline. This too is a false narrative that imposes barriers to students from marginalized groups.

Racial talk among STEM learners has been documented in a number of studies (Nasir et al., 2009; Schaffer & Skinner, 2009; Shah, 2013). Students sometimes engage in racial talk to make sense of educational phenomena like performance patterns. Because race is widely considered a taboo topic (Pollock, 2004), such talk tends to take place in more private spaces away from a teacher. However, given the way race and racism saturate many societies around the world (Bonilla-Silva, 2003; Essed, 2002; Telles, 2004), educators can presume – even if they have not observed it directly – that their students are participating in racial talk related to computing.

This particular vignette was adapted from data collected in a study of racial discourse among students in mathematics (Nasir & Shah, 2011). There are strong similarities between mathematics and computing with respect to racial patterns in performance, representation, and opportunities to learn. For that reason, although studies of racial discourse specific to computing have yet to be conducted, we might reasonably expect similar forms of racial talk among computing students. To some, John's statement might seem like a harmless joke. However, this kind of superficial interpretation ignores the harm that racial narratives about STEM ability can cause (McGee & Martin, 2011; Shah, 2017). Instead, we can understand John's statement as a *microaggression*. According to psychologist Derald Wing Sue and colleagues (2007), "racial microaggressions are brief and commonplace daily verbal, behavioral, or environmental indignities, whether intentional or unintentional, that communicate hostile, derogatory, or negative racial slights and insults toward people of color" (p. 271). Certainly, microaggressions are not only racial; research has found evidence of microaggressions related to gender, religion, class, and other social markers (Sue et al., 2007).

John's statement functions as a racial microaggression through the deployment of multiple racial narratives about computing ability, including the false notions that Asian people have a natural ability for computing and that Latinx people are less competent in computing. These racial narratives cause harm in a couple of ways. First, they distort and narrow the types of identities available to students of color in computing. For Asians, the "Asians are naturally good at computing" narrative suggests that Asian students can *only* succeed in technical fields. Research shows that awareness of racial narratives about Asians having superior ability in STEM in the US context is widespread (Cvencek et al., 2015; Shah, 2017; Trytten et al., 2012). Further, this can exert undue pressure on Asian students to fulfill the narrative.

For Latinx people, and perhaps for non-Asian people of color more broadly, the narratives undermine the possibility of their success in computing. Instead, certain groups of color are pigeonholed into identities of underperformance. In this vignette, Marcos's Latinx identity is wrongly put in opposition to an identity as a successful computing learner, as if these identities cannot coexist. Whereas associations of Asians as "nerds" seem normal, such cultural representations for people of color cause dissonance and are rare in pop culture (Eglash, 2002). Racial narratives about Asians exacerbate the positioning of non-Asians of color as less capable in computing. In that sense, racial narratives are relationally linked in ways that produce false racial hierarchies of ability in a domain (Shah, 2017).

Second, John's microaggression also causes harm to the discipline of computing itself. By attributing Marcos's success to an "Asian gene," John reproduces the false idea that success in computing depends on an innate capacity for the subject. Given that race itself is often incorrectly viewed as a genetic trait (Gould, 1996), it is perhaps unsurprising that racial talk in STEM and discourses of innate ability often go hand in hand. In doing so, racial talk can perpetuate perceptions of computing as a domain reserved for certain groups and not others.

2.3.2 Recommendations

Overall, computing educators need to recognize that CEd exists within a racial context that influences how students perceive their own and their classmates' performance. Computing is not immune or divorced from the influence of race in society writ large. Educators should not ignore deployments of racial talk that further marginalize students of color; they must intervene.

One possible response is to make an immediate and direct verbal intervention that clearly states that race, gender, or any other social marker has no bearing on computing ability. It is important that students hear unequivocal statements about this from their computing instructors, since students see these people as authorities in the field. A private conversation with the students who were involved can signal to them the gravity of such "jokes." Beyond addressing those students, though, it can be impactful to have this discussion with the whole class as well. Other students may have overheard and been influenced by the interaction, and even if they were not, all students – but especially non-Asian students of color – must know for certain that their instructor believes in their capacity to succeed in computing.

Of course, situations like these can be awkward for instructors, and it may be challenging or uncomfortable to intervene in the moment. However, it is not necessary to respond immediately. Just as instructors provide students wait time before responding to a question in a class discussion, it can be productive to reflect on the interaction and revisit the interaction with students later during office hours or during the next class session.

In addition to verbal interventions, instructors can take steps to begin shifting the cultural narratives themselves about who can succeed in computing. For example, research shows that the physical artifacts in a computing classroom (such as a Star Trek poster) can send signals about who belongs in computing (Cheryan et al., 2009). How can a classroom space be organized in ways that signal inclusion? Continual exposure to images of computer scientists from marginalized groups is one way of doing this (see Shah et al., 2013). While we acknowledge that cultural narratives have considerable inertia and are difficult to change, we argue that this is one simple, concrete action missing from many computing classrooms that would foster equity.

2.4 Ways We Can Validate and Improve Students' Experiences of Bias

Suzanne, a student in your Data Structures class, has come to your office hours to discuss a concept from that week's lecture. After discussing it with her for a few minutes, Suzanne begins to tell you about her experience in the class: "When I'm in lab and we're working in groups, the men in my group never listen to my ideas. The guys just turn toward each other and never ask me for help or my input. When I say something, they just ignore me."

2.4.1 Vignette Analysis

Despite the preponderance of evidence of sexism in computing and in society, some instructors might still feel that Suzanne is exaggerating – that "it's all in her head" – or that the incident was not as significant as Suzanne feels. Others might feel that she is playing the "gender card" to cover for being less competent than her male peers. Further, if one assumes that Suzanne is actually less competent, an instructor might feel that her peers should not be expected to seek out Suzanne's input. Overall, such interpretations reify false gender narratives about computing ability and diminish the continued impact of patriarchy in everyday life, including computing learning contexts. Honoring students' experiences requires educators to ask themselves the following question: Do I have the right to judge the validity of my students' experiences? With respect to gender issues in computing, given that the field is dominated by men, this is a particularly pressing question.

Many computing educators have themselves had positive experiences in learning computing. However, we must acknowledge that some of our students may be having different experiences. Research shows that people from historically marginalized groups in STEM tend to have categorically different experiences from people from dominant groups (Harper & Hurtado, 2007; McGee & Martin, 2011; Stinson, 2008). Computing educators need to both honor students' experiences as learners and also realize that their own positive experiences with computing can obfuscate an appreciation for their students' negative experiences.

In Suzanne's case, her experience of being marginalized by men in her group aligns with research documenting sexism in computing (Cohoon et al., 2009; Margolis & Fisher, 2003). Similar to the previous vignette, the experience of being ignored and having one's ideas dismissed or not solicited in the first place constitutes a microaggression (Sue et al., 2007). The men in Suzanne's group do not make overtly sexist comments, but Suzanne interprets their talking only to each other as a sexist move; this is her experience and must be taken seriously. Of course, these men might not have realized they were ignoring Suzanne. While it is possible that these students were overtly and intentionally sexist, it is also possible that their behavior was the unintentional result of implicit gender biases they held about women in computing and in general. In either case, students need opportunities to learn about how inequity operates in regular classroom interactions and what they can do to mitigate how they contribute to such inequities.

2.4.2 Recommendations

Before considering pedagogical responses to Suzanne's story of marginalization, instructors can do something simple but impactful to support students from marginalized groups: believe them. It takes courage for students to share such experiences with their instructors, especially when those instructors belong to dominant groups. Believing in the possibility that students' self-reports of inequity have merit validates students' subjective experiences. Further, the risk of harm with such inequities is so great that it behooves instructors to take reports of them seriously. One concrete way to show this is to actively listen to students' experiences without evaluating those experiences. Instructors have considerable power in the instructor–student relationship, so listening without judgment is critical to managing students' vulnerability.

Beyond listening without judgment, students may want their instructors to take some kind of action. In our experience, it is okay to tell students that you will think about what they have shared and follow up with them with potential solutions. It also can be empowering to work collaboratively with the student to think of solutions that might work for them. Regardless, following up with students after an initial meeting can assure them that you have not forgotten about what they shared and are taking it seriously. Finally, it is also important to maintain confidentiality (unless the incident falls under mandatory reporting statutes). Explicitly telling students that you will keep what they have told you confidential can be an important step in trust-building. It is particularly helpful to learn about your legal responsibilities for reporting so that you can clearly communicate these to students.

One issue here is that students from marginalized groups often do not feel comfortable sharing experiences of inequity with instructors, perhaps in part because of a fear that they will not be believed or that action will not be taken. Just because students have not shared stories about their negative experiences does not mean they are not happening. Instructors should actively implement ways for students to report such incidents – for instance, an anonymous survey given periodically throughout a course can be a way for students to report their experiences. This can also signal to students that they have an instructor that cares about equity.

Finally, efforts can be taken to educate students about how inequity operates in social interaction. For example, students can be given readings on implicit bias and microaggressions early in the course, coupled with class discussions about how these phenomena might come up in their particular class. Additionally, students might be required to take an Implicit Association Test (IAT) as part of an ungraded assignment – the results of the IAT might also be fodder for class discussion about inequity. Last, an institution might organize a training session around implicit bias for all of their students. This sends the message that the burden for addressing these inequities does not fall on students like Suzanne, but rather on students like her male group members. Companies like Google and Facebook have made their internal training modules on implicit bias available for free to the public (see Google's modules at https://rework.withgoogle.com/subjects/unbiasing and Facebook's modules at https://managingbias.fb.com). Associating learning about implicit bias with these companies may also reinforce the notion that this is important for students' professional training.

3 Open Questions

We now expand our focus and identify particular open questions, having already identified relevant terms in equity and diversity (Section 1.2) and summarized problematic narratives about computing and computer scientists (Section 1.3) and how these narratives cause harm through implicit bias (Sections 1.4 and 1.5). The vignettes above also introduced research about structural barriers and stereotype threat (Section 2.1), belonging and participation (Section 2.2), biased statements in the classroom and their impact (Section 2.3), and the importance of listening to students (Section 2.4).

3.1 Computing for What Purposes?

In this chapter, we have made certain assumptions about the goals of CEd in relation to issues of equity and inequity. By focusing on the social-interactional barriers faced by students from particular groups, we have assumed that increasing the number of women computer scientists and computer scientists of color, for example, is a worthy goal. Many educators and scholars within our field are in agreement on this, and we stand by this assumption. At the same time, though, we as a field must also take a critical stance on why people should learn computing in the first place.

There is an economic rationale for learning computing, in that computing can open access to high-paying jobs, which include jobs in the computing field and jobs that involve computing. For groups that have been systematically excluded from opportunities to accumulate wealth and are simultaneously targeted for state-sponsored plunder, the chance to attain financial stability through CEd is nontrivial. Working toward more computer scientists from marginalized groups is also a matter of cultural representation. Instances of bias in software that result in the propagation of white supremacy, patriarchy, and other forms of domination have been well documented (Rose, 2010; Tatman, 2016).

Presumably, greater demographic diversity in computing would mitigate such biases and lead to more inclusive and humane technologies. Overall, these are good reasons for greater equity in computing. And yet, pursuing equity only for the sake of capitalism or cultural representation can perpetuate inequity. We must question what we mean by "computing education" and our motivations for encouraging students to learn computing (Lewis, 2017).

Computing is not inherently good. Like anything else, it matters how we use it. Indeed, computing has been used to commit corporate fraud (Tabuchi & Ewing, 2016) and has also contributed to social injustice (O'Neil, 2016). STEM disciplines more broadly have long since been implicated in militaristic endeavors (Schoenfeld, 2004). What does it mean to push for equity in versions of CEd focused narrowly on producing technology for the sake of profit or that causes harm? Do we want more people of color or women in computing to do this kind of work? To what kinds of computing are we broadening participation?

In thinking about equity in CEd, it is imperative that as a field we expand the forms and goals of computing. Computing can be used for self-expression and to explore identities and cultural experiences (Eglash et al., 2013; Harrell, 2013; Kafai et al., 2014; Scott & White, 2013). Computing can also be used to understand the world better and foster justice in both students' local communities and society writ large (Vakil, 2014). A version of computing oriented toward the pursuit of social justice requires conceptualizations of equity that begin with an understanding of historical patterns of oppression and a deep analysis of sociopolitical values and goals (Martin, 2003; Vossoughi et al., 2016).

We encourage future research on equity and inequity in CEd to embrace and to develop versions of CEd that can lead to humanization and greater justice for people from marginalized groups.

3.2 Problematizing "Equity" Terminology

Language matters. As we discussed earlier, the language we use to describe marginalization and efforts to attenuate marginalization comes with various affordances and constraints. "Equity" and "diversity" are among the terms most preferred by the field. However, we must continue to question equity-related terminology in relation to our goals for CEd. In part, this involves pushing for specificity in how we deploy equity discourse. For example, "diversity" is a vague term. In writing and in presentations, it is important to specify what forms of diversity we are referring to at any particular time (e.g., racial diversity, linguistic diversity, gender diversity). Further, terms can become conflated in problematic ways, such as "equity" and "equality," and the use of "culture" and "urban" for "race."

Without specificity and clear intention, equity-related language risks becoming facile slogans devoid of real meaning (Apple, 1992). Scholars in other STEM disciplines have engaged with these issues. In mathematics education, for example, Martin (2003) has critiqued the persistent "mathematics for all" rhetoric as "broad and non-specific" (p. 13). Martin argues that the word "all" allows stakeholders in education to avoid naming social markers like race, which serves to obscure the specific needs and inequities experienced by members of particular marginalized groups. Similar rhetoric abounds in computing – what are the limitations of the "for all" language as a way to frame equity issues?

Future research in this area would be well served in asking: Is the language of "equity" and "diversity" adequately radical? In what ways does it reproduce what Gutiérrez (2008) has called "gap-gazing," which refers to an overemphasis on performance gaps between racial groups or gender gaps in participation along the CEd pipeline? Performance and participation are important foci, but CEd can and should engage with larger issues and questions. What does computing have to do with the murder of black people at the hands of the police, or how does computing contribute to – and how can it help in pushing back against – global Islamophobia? To what extent does the currently dominant equity-related discourse in computing make it possible to address questions of this kind? In posing these questions to the field, we simultaneously find ourselves asking them of ourselves and reflecting on what they mean for the directions of our own future work.

Language always has its limits. We do not believe that a "perfect" set of terms exist that cover all aspects of the complex problems of inequity and injustice. However, we feel it is important that the field not take terminology for granted – both in definition and in conceptual validity. We argue for an interrogatory stance toward equity-related language, particularly in relation to the goals of equity work in CEd.

3.3 Researching Equitable Practices

The pedagogies that we employ and the tools and environments in which they are positioned can have distinct implications for equity and students' opportunities to learn. There remain open questions that may help us build toward a more equitable culture of CEd. Here, we introduce two open questions that highlight some exciting recent work in CEd.

What role does culturally responsive pedagogy play? The Exploring CS curriculum (Goode et al., 2012; Margolis et al., 2015) explores social, creative, and culturally responsive computing contexts. Similarly, the work of Fields et al. (2017) and Kafai et al. (2014) explores ethnocomputing with e-textiles. Brady et al. (2017) use social and diverse computing contexts in addition to physical computing and maker technologies. Rubio et al. (2015) also adopt a physical computing approach, with their study closing the gap in gendered perceptions of the difficulty of computing and the desire to continue with computing learning opportunities. Medel and Pornaghshband (2017) explore the ways that gendered names, imagery, and language lead to gender bias in the curriculum. As these interventions and curricula are refined and evaluated, we look forward to learning how to effectively integrate culturally responsive pedagogies and curricula.

What characteristics of the intervention and context are necessary and sufficient for interventions that have been successful at fostering diversity (Alvarado et al., 2012; Falkner et al., 2016; Guzdial, 2013)? For example, Media Computation is an approach for teaching introductory computing through having students create and manipulate digital media. While this approach increased retention more broadly and girls found the content more motivating, there was no significant difference in learning gain for participants (Guzdial, 2013). In their Media Computation-based massive open online course (MOOC), Falkner et al. (2016) report significantly higher enrollment by female students (34 percent) than typically reported for computing MOOCs. Collaborative and active learning pedagogies have been effective in promoting increased learning outcomes (Prince, 2004). However, collaborative pedagogies have also been shown to lead to marginalization (Lewis & Shah, 2015). There is a lot that remains to be explored in the design of effective and equitable curricula and pedagogies.

4 Conclusion

In our use of vignettes, we have focused on a contextualized review of the literature. The work we decided to foreground was intentional, but still we regret not being able to include more context, information, and resources. We hope that our readers will use the chapter as a jumping-off point to continue to explore these important issues and how they can improve their current context in pursuit of equity and justice.

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