Race and Collaboration in Computer Science: A Network Science Approach

Dr. Crystal E. Peoples, Duke University

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

Alicia Nicki Washington, Ph.D., Duke University

Dr. Nicki Washington is a professor of the practice of computer science and gender, sexuality, and feminist studies at Duke University and the author of Unapologetically Dope: Lessons for Black Women and Girls on Surviving and Thriving in the Tech Field. She is currently the director of the Cultural Competence in Computing (3C) Fellows program and the NSF-funded Alliance for Identity-Inclusive Computing Education (AiiCE). She also serves as senior personnel for the NSF-funded Athena Institute for Artificial Intelligence (AI). Her career in higher education began at Howard University as the first Black female faculty member in the Department of Computer Science. Her professional experience also includes Winthrop University, The Aerospace Corporation, and IBM. She is a graduate of Johnson C. Smith University (B.S., '00) and North Carolina State University (M.S., '02; Ph.D., '05), becoming the first Black woman to earn a Ph.D. in computer science at the university and 2019 Computer Science Hall of Fame Inductee.

Shaundra Bryant Daily, Duke University

Shaundra B. Daily is a professor of practice in Electrical and Computer Engineering & Computer Science at Duke University and Levitan Faculty Fellow, Special Assistant to the Vice Provosts. Prior to joining Duke, she was an associate professor with tenure at the University of Florida in the Department of Computer & Information Science & Engineering. She also served as an associate professor and interim co-chair in the School of Computing at Clemson University. Her research focuses on the design, implementation, and evaluation of technologies, programs, and curricula to support diversity, equity, and inclusion in STEM fields. Currently, through this work, she is the Backbone Director for the Alliance for Identity-Inclusive Computing Education as well as Education and Workforce Director for the Athena AI Institute. Having garnered over $40M in funding from public and private sources to support her collaborative research activities, Daily's work has been featured in USA Today, Forbes, National Public Radio, and the Chicago Tribune. Daily earned her B.S. and M.S. in Electrical Engineering from the Florida Agricultural and Mechanical University – Florida State University College of Engineering, and an S.M. and Ph.D. from the MIT Media Lab.

RACE AND COLLABORATION IN COMPUTER SCIENCE: A NETWORK SCIENCE APPROACH

INTRODUCTION

An important step in creating more equitable and inclusive CS departments is acknowledging that structural racism persists (and in some instances, thrives) in academic computing environments [1]–[4]. In many ways, faculty from racial groups that are historically underrepresented in computing (i.e., Black, Latinx, Native American, and Native Hawaiian or Pacific Islander) experience similar issues as students of the same identities (e.g., discrimination from students, faculty, and staff; campus policing; microaggressions, and other policies and practices that are inherently exclusive [5]–[7].

Scholars are often marginalized when publishing academic papers, facing numerous obstacles and systemic barriers that can impede their academic success [8]–[10]. Research demonstrates that racial identity impacts whose work is considered scientific knowledge, reinforcing "idealized notions of meritocracy in science" [11]. Scholars often encounter biased peer review processes, limited access to publishing outlets, lack of citations of their published work, and a lack of funding to support their ability to progress in their careers [12]–[16]. Moreover, their underrepresentation results in a limited pool of potential reviewers, making it more difficult to ensure fair and unbiased peer reviews. As a result, valuable perspectives and research are overlooked and underrepresented in academic discourse, perpetuating inequalities and inequities and further hindering progress in various fields such as computer science (CS), where roughly 82% of scholars are white and Asian [17].

Scholars also report being excluded from opportunities for collaborative research with white counterparts [18]. Additionally, biased views of what is considered "valid" CS research and who is centered as experts on topics related to CS education and DEI-based research result in harmful policies, practices, and cultures that disproportionately impact scholars who are not members of dominant racial groups [19]. While the push for greater representation of scholars from diverse demographic groups is needed, if the harmful culture of exclusion and denigration of the work of those who are minoritized in computing is not addressed, then the impact of such initiatives will be minor. Faculty from minoritized groups often cite toxic relationships with white colleagues as a primary reason for leaving an institution [20]. This mirrors research on the experiences of tech employees who leave the industry due to toxic environments [21].

Collaboration and publishing are key facilitators of an individual scholar's success in the academy, as well as the consumption, production, and diffusion of knowledge in the overall field [22]. Thus, an important area of exploration is how much race and collaboration, partial functions of the culture of a department and field, impact the trajectories of scholars from groups that are historically underrepresented in computing.

MOTIVATION

Collaboration networks are a type of graph where authors are represented as nodes and the edges between them represent shared publications. There is rich literature that explores collaboration by discipline, institutional affiliations, geographic locations, and the career status and gender composition of the team [23]–[26]. These studies examine the growth patterns in scientific collaboration; the research impact of increasing collaboration (measured as co-authorship); how these patterns differ by discipline; and how they relate to the uniqueness of the contribution (for a review, see [22]).

Collaboration rates are on the rise, as are the number of studies on the process of scientific collaboration. Scholars have become increasingly clustered into distinct collaboration networks or communities across their fields. This collaboration is partially patterned by the culture of the profession [27]. In CS, where a scholar is located in the overall collaboration space has been linked to citation counts and overall impact on the field [28]. Social scientists who study knowledge production and diffusion have shown that social interaction plays a significant role in the production and acceptance of new knowledge claims [29]–[31]. Therefore, CS collaboration networks tell more than the patterns of computer scientists' publications; they (can) speak to *which* ideas spread, *how* they spread, *whose* ideas spread, *how long* before they are ultimately accepted (or not), and *if* they influence the direction of the field. These missing pieces are crucial to understanding the development of the field and what knowledge becomes privileged within a racialized social system.

Network scientists have repeatedly shown that social networks, including collaboration networks, tend to be racially segregated [32]. However, this segregation is often incorrectly attributed to "personal choice" rather than a structural effect of the racialized society in which people live. Therefore, access to (racialized) networks is unequal across individuals based on their racialized position in society. As social capital, or resources a person can access over others, is embedded in network relationships [33], [34], network segregation plays a considerable role in the (re)production of racial inequalities. For example, most recruitment strategies occur through informal social networks and tend to be more effective for white people than minoritized groups [35]. This otherwise "hidden" structural mechanism contributes to the fact that the representation of these excluded groups in the CS discipline (including industry) has only slightly increased, despite efforts to improve it [21], [36], [37].

In CS, several studies discuss how the discipline's network has evolved over time, showing overall changes in various measures of the discipline's collaboration structure using publication data from bibliometric databases such as *The DBLP Computer Science Bibliography* [38], CiteSeer, and the Semantic Scholar Open Research Corpus [28], [39]–[43]. This work revealed that while the average number of unique collaborators of a CS scholar increased from 1.9 to 6.6 average coauthors per scholar from the 1960s to early 2000s, this growth rate has slowed. The average number of collaborators in 2014 was 6.47 [28], [39]. The average CS journal paper has only two or three authors versus conference papers that have significantly more coauthors.

As collaboration on published work becomes increasingly common in CS, the overall field's collaboration network structure has begun to show distinct clustering into specific communities. Highly segregated communities, or small groups that have a larger distance from the rest of the network, in CS tend to be located in the network periphery of the CS space and receive fewer citations than non-segregated communities [28]. However, none of these studies of the CS collaboration space have seriously questioned *why* the network structure looks the way it does and have only minimally discussed the implications these collaboration structures have on the lived experiences of scholars in the field (e.g., as it relates to their citation count, academic prestige, and career progression).

The above discussion led to the hypothesis that the CS collaboration networks in the literature were overly representative of the collaboration networks of white and Asian scholars in computing. By extension, reported network measures such as degree (or the average number of unique coauthors) would not be reflective of the collaboration experiences of non-white and Asian computer scientists. Further, this work posited this difference would skew in favor of white and Asian scholars. That is, if the "average" (e.g., race-neutral approach) computer scientist has *x* number of unique collaborators, then minoritized computer scientists will have fewer, due to their marginalization in the field.

This research extends existing literature by discussing the role of collaboration networks, as one form of social capital, in creating and/or exacerbating inequalities/inequities in CS. Since the discipline has an intricate history of racial exclusion [44], this research posits there will be structural differences in the collaboration networks formed by scholars who have been historically underrepresented in computing compared to those of white and Asian scholars. Using sociological theories of race and racism, this paper begins to explore the relationship between race and collaboration in computing environments to uncover a new mechanism that contributes to the persistence of racial inequality in the field.

METHODS

A list of Black and Latinx computing doctorate recipients (n = 144) were obtained using prior research on Black faculty in CS research departments [45] and information from the *Hispanics in Computing* website [46]. Individuals from [45], [46] were solely identified as Black or Latinx computing scholars, so this research retained those labels in the analyses that follow and cannot ascertain if there were any Afro-Latinos in the sample. The individuals in the study received their doctorates from 1976 to 2021; however, most of the doctorates were obtained between 2002 and 2016. All Black doctorate recipients in this study were tenure-track faculty at Research 1 institutions. Similarly, most of the Latinx computing Ph.Ds. were also in the academy; however, six Latinx computing doctorates worked in industry instead. Due to the inability to obtain a list of Native American and Native Hawaiian/Pacific Islander graduates, the current work was limited to these two ethnoracial groups.

Using these names, Bibtex files were downloaded from *The DBLP Computer Science Bibliography* [38] in the fall of 2022 to obtain each author's (hereafter referred to as an *ego*) CS publication record. No limit was placed on the time frame of the publications gathered. As such, some scholars have significantly more publications than others simply due to their being in the field longer. The DBLP is an internationally respected database that compiles a wide range of publications that have been indexed as relevant to the computing community [47]. A collaboration network was then created for each ego in the sample by creating a vertex set of the ego and their coauthors (hereafter referred to as *alters*) and assigning an edge between them for every shared publication. The resulting networks were simplified and weighted according to the number of shared publications between every author pair. Typical network properties such as degree (the average number of unique coauthors), density (the proportion of possible co-authorships present), and constraint (the degree to which scholars can coauthor without the individual in the sample) were investigated and compared to analogous measures reported in the discipline's overall collaboration networks that have neglected to consider race [28], [39].

Since collaboration networks are social capital, multiple network measures corresponding to social capital were analyzed [33], [34]. The three social capital variables used in this work were an ego's degree, network density, and constraint. Degree represents an ego's number of unique alters. Density refers to the proportion of all present collaboration ties over all possible ties in the network. Burt's constraint is a measure of the alternative authors for collaboration with alters other than the ego [48]. In general, the higher the degree of an ego, the greater the density of an ego's network. Conversely, the lower the ego's constraint, the higher the level of social capital they possess.

RESULTS AND DISCUSSION

This convenience sample included 106 Black and 38 Latinx CS doctorate recipients. This research was a first step towards gaining an understanding of potential differences in collaboration by ethnoracial groups in CS. As such, convenience sampling and the results herein were appropriate for gaining a sense of the state of collaboration in the field for minoritized scholars. The sample included more representation of Black graduates than Latinx by almost 2.5 to 1, despite the most recent estimates from the Taulbee survey indicating that Black and Latinx scholars obtain CS PhDs at approximately the same rate [17]. The Bibtex files for six members of the sample (two Black and four Latinx) did not have any publications listed in the DBLP. Consequently, there were six fewer collaboration networks created. The results that follow were obtained from the remaining 138 ego networks.

Table 1 shows the results of the three social capital variables (degree, density, and constraint) for each ethnoracial group and the overall sample. The average degree for Black CS scholars was (61.5, $\sigma = 55.9$), which was slightly higher than the average degree for Latinx CS scholars (54.6, $\sigma = 65.1$). The overall sample had an average degree of 59.833 ($\sigma = 58.131$), which means that the average computer scientist in this sample had nearly 60 unique collaborators. The average degree reported in previous research for all computer scientists in the discipline ranged from 5.53 to just under 20, depending on the data and time period used [28], [39]. Thus, the average Black/Latinx computer scientist in this sample had at least three times as many collaborators as the average of all computer scientists in the field. While these findings could partially be attributed to the individuals in this research's sample being particularly productive because they are primarily at R1 institutions, this alone cannot explain all these differences.

Table 1. Structural properties of ego collaboration networks

	Black (n = 104)	*Latinx* (n = 34)	*Total Sample* (n = 138)	*The Entire CS Field* [28], [39]
Social Capital				
Degree	61.5 (55.9)	54.6 (65.1)	59.833 (58.131)	[5.53, 20)
Density*	0.199 (0.142)	0.368 (0.321)	0.241 (0.213)	-
Constraint	0.122 (0.127)	0.278 (0.325)	0.160 (0.205)	-

$^{*}p < 0.05$

Another property of interest in network research is that of the degree distribution of authors. In most real-world networks (collaboration or otherwise), the degree distribution of the network is highly right skewed. In this sample, most collaboration networks were comprised of egos with very few alters; however, there were a small number of egos with many alters. Figure 1 shows the resulting degree distribution from the egos in this sample. In the overall computing collaboration network reported by [39], approximately 50% of scholars had one to three unique alters (represented by the red line in Figure 1), with only 28 authors having more than 300 alters. As shown in Figure 1, this sample had a median degree of 43.5 alters (represented by the blue dashed lined in Figure 1). This further supports the finding that the Black and Latinx scholars in this sample collaborated with significantly more scholars than the typical CS scholar.

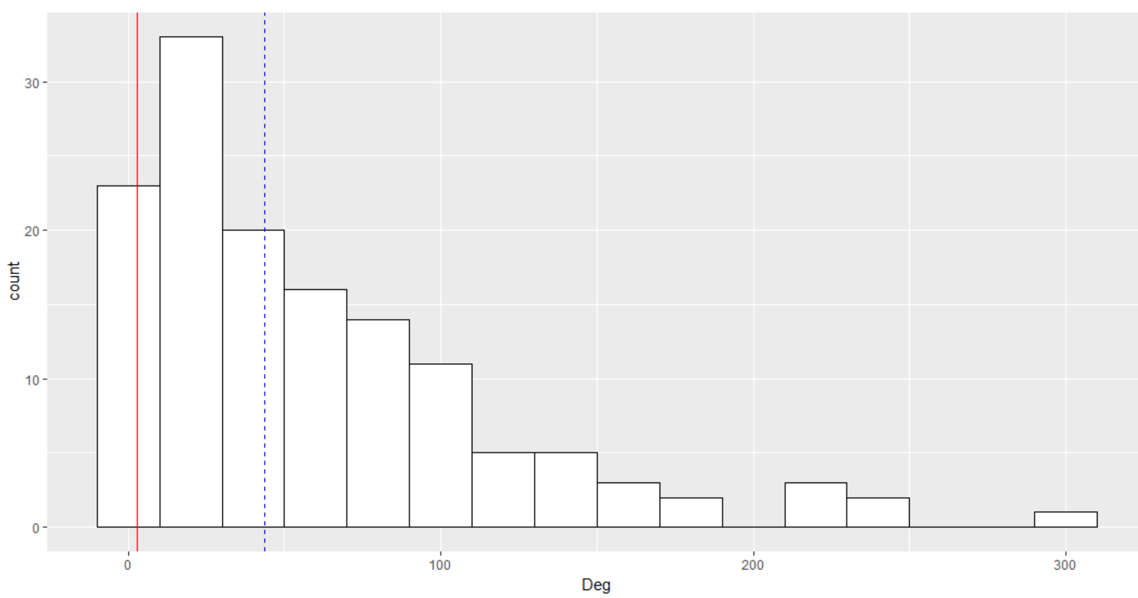

Figure 1: Degree Distribution of Sample

Figure 1 also shows that this sample contained 25 egos with a degree of at least 100 alters, one of whom had over 300. Egos such as these with remarkably high degrees are often referred to as "hubs." Hubs tend to have tremendous social capital in their fields, since they have direct access to many other scholars and are better able to proficiently spread and receive information. This sample had many hubs, which indicates the people in this sample *should* have access to some of the best resources (via people) the field has to offer. However, this research has focused on the individual networks of these scholars without putting them in the context of the larger CS collaboration space. Given the history of racial exclusion in CS, these network hubs could be more isolated from other network hubs in the collaboration space with the kind of access and resources needed in the field. Additionally, there is a higher likelihood that the alters in these networks are also largely minoritized scholars [32]. While this would likely lead to a greater sense of belonging in the CS space for the egos and their alters [49]–[51], it is unclear what effect this would have on their ability to extract further resources in the larger CS space. Future qualitative research on the network hubs in this sample could uncover more information about their social capital and opportunities.

Density, the second social capital variable, showed significant differences between Black and Latinx computer scientists. Black computer scientists had a smaller average density of 0.199 (σ = 0.142) to that of Latinx computer scientists at 0.368 (σ = 0.321). This finding was statistically significant, indicating that Latinx computer scientists had more social capital on this measure than Black computer scientists. Practically, this difference could mean several things. First, this could indicate that Latinx computer scientists have stronger connections with the people they collaborate, since they have more connections than do Black computer scientists. Second, this could also indicate that Latinx computer scientists produce more innovative work than do Black computer scientists, since previous studies have found a link between density and innovation [52]. However, other studies have found the opposite [53], so this finding could instead indicate that Black computer scientists produce more innovative work than do Latinx computer scientists. Ultimately, the density calculation should not be considered without also taking into account the number of alters (coauthors) that each author has. As shown in Figure 2, the network with the greatest density (1.0) has only one collaborator which is not typically considered to be a fruitful network of collaborators. Future work should be done to uncover what these connections mean for the computer scientists involved in this study.

The overall sample's density was 0.241 (σ = 0.213). However, these density figures cannot be compared to previously reported densities of the CS collaboration network space overall. Densities that have been reported in [28], [39] are for the entire field, and these figures tend to be small given the large number of possible collaborations for everyone in the field. However, ego network densities can be expected to be reasonably larger, since the vertex set is limited to the number of alters the ego has, thus making the total number of possible collaborations significantly smaller.

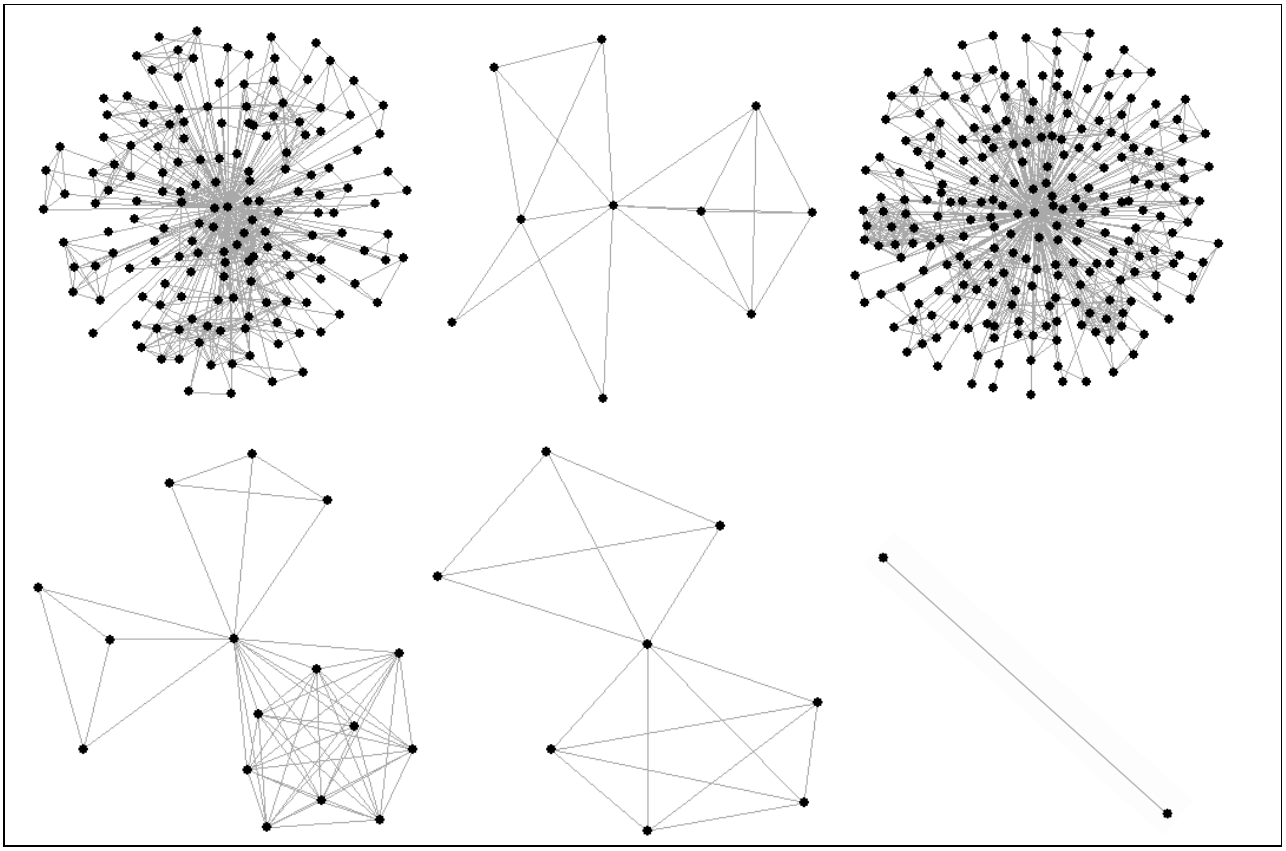

Figure 2: Sample of Six Collaboration Networks, Arranged Top-Left to Bottom-Right by Increasing Density

Constraint, which gauges an ego's alters' abilities to collaborate without them, was the third social capital variable measured. As shown in Table 1, Black computer scientists had less constraint (0.122, $\sigma = 0.127$) than Latinx computer scientists (0.278, $\sigma = 0.325$). Substantively, this means that the alters of the Latinx scholars in this sample had more ability to collaborate with one another and exclude the ego in future collaborations than did the alters of Black scholars. The average constraint for the sample overall was 0.160 ($\sigma = 0.205$). Unfortunately, the existing literature does not calculate constraint measures on the overall field, as they have only discussed more global network properties, such as overall clustering (finding densely connected but relatively isolated subnetworks from an overall network) in the field. Since this research contends that the individuals within these networks must also be discussed, the social capital measures used here are more appropriate for these questions.

The results from Table 1 indicate a few things. First, Black and Latinx scholars from this sample had significantly more alters (coauthors) than the "average" computer scientist, as reported in the literature. Given their marginalization in the field, this research expected the opposite finding of fewer alters for Black and Latinx scholars. However, this finding suggests the need for an alternative explanation. As previously mentioned, this finding is partially explained by the research sample itself; however, there are more salient factors likely involved in the explanation of these differences. These findings suggests that Black and Latinx scholars may have internalized the idea that “twice as good isn’t enough” [54]: To be successful in computing, they must diversify their collaborators significantly more than their white and Asian counterparts. Second, this research also suggests that collaboration styles are different for Black and Latinx scholars in CS. While the number of alters each group has is similar, they have very different network densities. Thus, their styles of collaboration are likely different. For example, Latinx CS scholars had greater densities in their collaboration networks than Black CS scholars. This could indicate that Latinx scholars work within the same groups repeatedly, slowly bringing in additional coauthors over time, while Black scholars may diversify collaborations more. Alternatively, this finding could be specific to this sample, since the Latinx scholars pool is small (n =34). More research should be done to ascertain experiences that are unique to each group that could influence the differences identified.

STUDY LIMITATIONS

There are several limitations to the study to consider. First, this study relied on a convenience sample of Black and Latinx scholars from prior research, and the sample is disproportionately composed of more Black CS scholars than Latinx CS scholars. As such, the 138 scholars used in this study may not be an accurate representation of Black and Latinx scholars in computing as a whole. Instead, this may reflect the networks of a small group of highly resourceful and resilient members of this community. Future research should examine other factors related to collaboration in CS (e.g., age of the researcher, institution type, and rank) to understand how these influence (or do not) collaboration networks. Second, this research was not able to examine the collaboration networks of Native American, Native Hawaiian, or Pacific Islander scholars in CS. Therefore, the research cannot comment on the collaboration experiences of these groups. Third, the publication data used in this study (obtained from the DBLP) may not be exhaustive of the work of the scholars in the sample. While many informatics researchers commend the database for its accuracy and thoroughness (and prior research on this topic has used information from this database [39]), the DBLP acknowledges a prioritization of “the inclusion of venues based on their scientific merit and importance to the computer science community...[including] hybrid fields as long as they are of significant interest to the computer science research community” [47]. This includes a concentration on English language articles, indexing articles submitted by conference chairs and journal editors, and not processing certain publications if the advisory board questions the scientific merit of the work. Given known bias in what is considered “valid” CS research that disproportionately affects these groups [9]–[11], there are likely publications missing from the sample’s works and, therefore, are not included in their collaboration network calculations. Fourth, this study did not comment on other relevant factors in publications such as the average number of authors per publication or the authorship order of the collaborators on their publications. Since these factors give publications more or less “weight” in the professional development of an individual, future research should study these metrics and discuss any effects they may have on the persons in the sample. Given the above limitations, however, these factors only further highlight the need for future work on race in computing. If success for groups that are historically underrepresented in computing means being three times as collaborative as the average white and Asian scholar, then efforts to create a more diverse, equitable, and inclusive computing field still have much work to do.

CONCLUSION

Since research correlates collaboration networks with scholarly productivity, citation counts, and career development and success, this analysis demonstrates the impact that a lack of diversity in CS has on Black and Latinx scholars and further provides opportunities to influence future intervention strategies designed to correct hidden mechanisms impeding their successes. While previous research examined the structure of computing collaboration networks, no studies have examined the structure as it relates to race. Since computing is dominated by white and Asian scholars, reports on the "average" computer scientist's collaboration network will be skewed to what their networks reflect. This study highlights the importance of opening this discussion to understand a potential structural barrier to historically underrepresented groups in computing. This study discovered the importance of strong collaboration networks in computer science for Black and Latinx scholars and showed that the sampled scholars have at least three times as many unique collaborators as the average computing scholar. While this study cannot answer the important question of *how* or *why* these collaborations came to be formed, the research does offer further support for the theory that computing is not a race-neutral field. When historically underrepresented groups of computer scientists have significantly different collaborations than those of their white and Asian counterparts (and yet, remain grossly underrepresented), the culture of the field must be analyzed. Until computing, particularly within the academy, acknowledges, understands, and begins to take seriously these important topics (and the discipline's complicity in the perpetuation of a culture that marginalizes Black and Brown scholars), racial disparities will continue to plague the field.

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REFERENCES

[1] E. O. McGee, "Interrogating Structural Racism in STEM Higher Education," *Educational Researcher*, vol. 49, no. 9, pp. 633–644, Dec. 2020, doi: 10.3102/0013189X20972718.

[2] Y. A. Rankin, J. O. Thomas, and S. Erete, "Real Talk: Saturated Sites of Violence in CS Education," in *Proceedings of the 52nd ACM Technical Symposium on Computer Science Education*, Virtual Event USA: ACM, Mar. 2021, pp. 802–808. doi: 10.1145/3408877.3432432.

[3] E. W. Huff *et al.*, "Going Through a Process of Whitening: Student Experiences Within Computer Science Education," in *Proceedings of the 52nd ACM Technical Symposium on Computer Science Education*, in SIGCSE '21. New York, NY, USA: Association for Computing Machinery, Mar. 2021, p. 1348. doi: 10.1145/3408877.3432497.

[4] S. T. Jones and N. Melo, "'Anti-blackness is no glitch': the need for critical conversations within computer science education," *XRDS*, vol. 27, no. 2, pp. 42–46, Dec. 2020, doi: 10.1145/3433134.

[5] C. Sadler, A. N. Washington, and S. B. Daily, "Work in Progress: A Novel Professional Development Program for Addressing Systemic Barriers to Computing Participation," presented at the American Society for Engineering Education, Minneapolis MN USA, Minneapolis MN USA, Jun. 2022.

[6] Langin, K., "A sense of belonging matters. That's why academic culture needs to change," Jnauary 2019. https://www.science.org/content/article/sense-belonging-matters-s-why-academic-culture-needs-change (accessed Jan. 30, 2022).

[7] J. R. Stark, "Black and African American Women Postdocs in STEM: Their Experiences and Career Plans," Ed.D., University of Pennsylvania, United States -- Pennsylvania, 2021. Accessed: Jan. 30, 2022. [Online]. Available: https://www.proquest.com/docview/2572582316/abstract/1D6772B35B5F423CPQ/1

[8] I. H. Settles, M. K. Jones, N. T. Buchanan, and K. Dotson, "Epistemic exclusion: Scholar(ly) devaluation that marginalizes faculty of color," *Journal of Diversity in Higher Education*, vol. 14, pp. 493–507, 2021, doi: 10.1037/dhe0000174.

[9] D. D. Bernal and O. Villalpando, "An apartheid of knowledge in academia: The struggle over the" legitimate" knowledge of faculty of color," *Equity & excellence in education*, vol. 35, no. 2, pp. 169–180, 2002.

[10] H. Admin, "Discrimination and a struggle for legitimacy: Faculty of color and female faculty experience an uneven playing field – HERI." https://heri.ucla.edu/news/press-releases/discrimination-and-a-struggle-for-legitimacy-faculty-of-color-and-female-faculty-experience-an-uneven-playing-field/ (accessed Jan. 30, 2022).

[11] C. Flaherty, "How Identity Shapes Science," *Inside Higher Ed*, Jan. 04, 2022. https://www.insidehighered.com/news/2022/01/04/new-data-how-race-and-gender-shape-science (accessed Jan. 30, 2022).

[12] I. H. Settles, N. T. Buchanan, and K. Dotson, "Scrutinized but not recognized: (In)visibility and hypervisibility experiences of faculty of color," *Journal of Vocational Behavior*, vol. 113, pp. 62–74, Aug. 2019, doi: 10.1016/j.jvb.2018.06.003.

[13] J. Cohen, "The Queen of the Social Sciences: The Reproduction of a [White] 'Man's Field,'" *History of Political Economy*, vol. 54, no. S1, pp. 259–282, Dec. 2022, doi: 10.1215/00182702-10085730.

[14] K. A. Griffin, "Institutional Barriers, Strategies, and Benefits to Increasing the Representation of Women and Men of Color in the Professoriate," in *Higher Education: Handbook of Theory and Research: Volume 35*, L. W. Perna, Ed., in Higher Education: Handbook of Theory and Research. Cham: Springer International Publishing, 2019, pp. 1–73. doi: 10.1007/978-3-030-11743-6_4-1.

[15] M. A. Taffe and N. W. Gilpin, “Racial inequity in grant funding from the US National Institutes of Health,” *eLife*, vol. 10, p. e65697, Jan. 2021, doi: 10.7554/eLife.65697.

[16] F. Z. Belgrave, M. P. Moore, and N. E. Douglas-Glenn, “Barriers and assets to external funding for African American faculty,” *International Journal of Qualitative Studies in Education*, vol. 32, no. 10, pp. 1250–1269, 2019.

[17] S. Zweben and B. Bizot, “2021 Taulbee Survey: CS Enrollment Grows at All Degree Levels, With Increased Gender Diversity,” Computing Research Association, May 2022. [Online]. Available: https://cra.org/wp-content/uploads/2022/05/2021-Taulbee-Survey.pdf

[18] K. A. Rockquemore and T. Laszloffy, *The Black Academic’s Guide to Winning Tenure -- Without Losing Your Soul*. Boulder, CO: Lynne Rienner Publishers, 2008.

[19] Washington, A.N. and DeLyser, L.A., “Planning for Change: Identifying and Addressing the DEI Challenges in SIGCSE,” ACM Special Interest Group in Computer Science Education Technical Symposium, ACM Special Interest Group in Computer Science Education Technical Symposium, 2021.

[20] R. E. Zambrana, *Toxic Ivory Towers: The Consequences of Work Stress on Underrpresented Minority Faculty.* New Brunswick, NJ: Rutgers University Press, 2018.

[21] A. Scott, F. Kapor Klein, and U. Onovakpuri, “Tech Leavers Study: A First-of-its-kind Analysis of why People Volunarily Left Jobs in Tech.,” Kapor Center for Social Impact, 2017. [Online]. Available: https://mk0kaporcenter5ld71a.kinstacdn.com/wp-content/uploads/2017/08/TechLeavers2017.pdf

[22] K. L. Hall *et al.*, “The science of team science: A review of the empirical evidence and research gaps on collaboration in science.,” *American Psychologist*, vol. 73, no. 4, pp. 532–548, May 2018, doi: 10.1037/amp0000319.

[23] Q. Ye, H. Song, and T. Li, “Cross-institutional collaboration networks in tourism and hospitality research,” *Tourism Management Perspectives*, vol. 2–3, pp. 55–64, Apr. 2012, doi: 10.1016/j.tmp.2012.03.002.

[24] R. K. Pan, K. Kaski, and S. Fortunato, “World citation and collaboration networks: uncovering the role of geography in science,” *Sci Rep*, vol. 2, no. 1, p. 902, Nov. 2012, doi: 10.1038/srep00902.

[25] J. D. West, J. Jacquet, M. M. King, S. J. Correll, and C. T. Bergstrom, “The Role of Gender in Scholarly Authorship,” *PLoS ONE*, vol. 8, no. 7, p. e66212, Jul. 2013, doi: 10.1371/journal.pone.0066212.

[26] X. H. T. Zeng *et al.*, “Differences in Collaboration Patterns across Discipline, Career Stage, and Gender,” *PLoS Biol*, vol. 14, no. 11, p. e1002573, Nov. 2016, doi: 10.1371/journal.pbio.1002573.

[27] J. N. Parker and E. J. Hackett, “Hot Spots and Hot Moments in Scientific Collaborations and Social Movements,” *Am Sociol Rev*, vol. 77, no. 1, pp. 21–44, Feb. 2012, doi: 10.1177/0003122411433763.

[28] A. M. Jaramillo, H. T. P. Williams, N. Perra, and R. Menezes, “The community structure of collaboration networks in computer science and its impact on scientific production and consumption.” arXiv, Jul. 20, 2022. Accessed: Feb. 08, 2023. [Online]. Available: http://arxiv.org/abs/2207.09800

[29] T. Kuhn, *The Structure of Scientific Revolutions*. Chicago, IL: University of Chicago Press, 1970.

[30] D. Crane, *Invisible Colleges: Diffusion of Knowledge in Scientific Communities*. Chicago, IL: University of Chicago Press, 1972.

[31] J. L. Martin, “Power, Authority, and the Constraint of Belief Systems,” *American Journal of Sociology*, vol. 107, no. 4, pp. 861–904, 2002, doi: 10.1086/343192.

[32] M. McPherson, L. Smith-Lovin, and J. M. Cook, “Birds of a Feather: Homophily in Social Networks,” *Annu. Rev. Sociol.*, vol. 27, no. 1, pp. 415–444, Aug. 2001, doi: 10.1146/annurev.soc.27.1.415.

[33] P. Bourdieu, “The Forms of Capital,” in *Handbook of Theory and Research for the Sociology of Education*, J. Richardson, Ed., New York, NY: Greenwood Press, 1986, pp. 241–258.

[34] N. Lin, *Social Capital: A Theory of Social Structure and Action*. Cambridge, UK: The Press Syndicate of the University of Cambridge, 2001.

[35] S. McDonald and J. C. Day, “Race, Gender, and the Invisible Hand of Social Capital: Race, Gender, and the Invisible Hand of Social Capital,” *Sociology Compass*, vol. 4, no. 7, pp. 532–543, Jul. 2010, doi: 10.1111/j.1751-9020.2010.00298.x.

[36] S. Banjo and D. Bass, “On Diversity, Silicon Valley Failed to Think Different,” *Bloomberg.com*, Aug. 03, 2020. Accessed: Dec. 21, 2020. [Online]. Available: https://www.bloomberg.com/news/articles/2020-08-03/silicon-valley-didn-t-inherit-discrimination-but-replicated-it-anyway

[37] S. Betz, “DEI Efforts Help but Tech Industry Still Falls Short: Report,” Mar. 2022. Accessed: Feb. 23, 2023. [Online]. Available: https://builtin.com/diversity-inclusion/state-of-dei-in-tech-2022-results

[38] The DBLP Team, “The DBLP Computer Science Bibliography.” Dec. 2022. [Online]. Available: https://dblp.org/sml/release/dblp-2022-12-01.xml.gz

[39] M. Franceschet, “Collaboration in computer science: A network science approach,” *J. Am. Soc. Inf. Sci.*, vol. 62, no. 10, pp. 1992–2012, Oct. 2011, doi: 10.1002/asi.21614.

[40] C. Bird, P. Devanbu, E. Barr, V. Filkov, A. Nash, and Z. Su, “Structure and Dynamics of Research Collaboration in Computer Science,” in *Proceedings of the 2009 SIAM International Conference on Data Mining*, Society for Industrial and Applied Mathematics, Apr. 2009, pp. 826–837. doi: 10.1137/1.9781611972795.71.

[41] E. Elmacioglu and D. Lee, “On six degrees of separation in DBLP-DB and more,” *SIGMOD Rec.*, vol. 34, no. 2, pp. 33–40, Jun. 2005, doi: 10.1145/1083784.1083791.

[42] J. Huang, Z. Zhuang, J. Li, and C. L. Giles, “Collaboration over time: characterizing and modeling network evolution,” in *Proceedings of the international conference on Web search and web data mining - WSDM ’08*, Palo Alto, California, USA: ACM Press, 2008, p. 107. doi: 10.1145/1341531.1341548.

[43] G. V. Menezes, N. Ziviani, A. H. F. Laender, and V. Almeida, “A geographical analysis of knowledge production in computer science,” in *Proceedings of the 18th international conference on World wide web*, Madrid Spain: ACM, Apr. 2009, pp. 1041–1050. doi: 10.1145/1526709.1526849.

[44] J. Goode, S. R. Johnson, and K. Sundstrom, “Disrupting colorblind teacher education in computer science,” *Professional Development in Education*, vol. 46, no. 2, pp. 354–367, Mar. 2020, doi: 10.1080/19415257.2018.1550102.

[45] J. E. Gilbert, J. A. M. Waisome, and S. Smarr, “An Analysis of Black Faculty in CS Research Departments,” *Commun. ACM*, vol. 66, no. 2, pp. 45–47, Feb. 2023, doi: 10.1145/3571279.

[46] “Hispanics in Computing,” 2023. https://hispanicsincomputing.org/ (accessed Feb. 23, 2023).

[47] The DBLP Team, “What is the scope of dblp?” https://dblp.org/faq/1474671.html (accessed Feb. 21, 2023).

[48] R. S. Burt, *Structural Holes: The Social Structure of Competition*. Cambridge, MA: Harvard University Press, 1992.

[49] A. Prewitt, W. Eugene, and S. Daily, “Minority retention and success in engineering: Diversifying the pipeline through the development of social capital,” presented at the 2007 Annual Conference & Exposition, 2007, pp. 12–1072.

[50] S. B. Daily, “Dancing In Virtual Environments: Alternative Pathways to Interest in Computin,” presented at the Virginia State University, Science, Technology, Engineering, Agriculture, Mathematics and Health Colloquium Series, Petersbug, VA, Petersbug, VA, Oct. 2013.

[51] S. Erete, C. K. Martin, and N. Pinkard, “Digital Youth Divas: A Program Model for Increasing Knowledge, Confidence, and Perceptions of Fit in STEM amongst Black and Brown Middle School Girls,” in *Moving Students of Color from Consumers to Producers of Technology*, IGI Global, 2017, pp. 152–173. doi: 10.4018/978-1-5225-2005-4.ch008.

[52] Y. Todo, P. Matous, and H. Inoue, “The strength of long ties and the weakness of strong ties: Knowledge diffusion through supply chain networks,” *Research Policy*, vol. 45, no. 9, pp. 1890–1906, Nov. 2016, doi: 10.1016/j.respol.2016.06.008.

[53] C. N. Gonzalez-Brambila, F. M. Veloso, and D. Krackhardt, “The impact of network embeddedness on research output,” *Research Policy*, vol. 42, no. 9, pp. 1555–1567, Nov. 2013, doi: 10.1016/j.respol.2013.07.008.

[54] A. N. Washington, “When Twice as Good Isn’t Enough: The Case for Cultural Competence in Computing,” in *Proceedings of the 51st ACM Technical Symposium on Computer Science Education*, Portland OR USA: ACM, Feb. 2020, pp. 213–219. doi: 10.1145/3328778.3366792.