Comparing Research Foci (What) and Student Participation (Who) in Computing Education Research in the United Kingdom and United States

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Abstract—**BACKGROUND. This full research paper focuses on understanding research foci (what) and student participants (who) in primary and secondary (K-12) computer science (CS) education research (CER). With the growing interest in CS education at primary and secondary schools, there is a growing body of research. Unfortunately, there is limited analysis of research against the broader education ecosystem. Given the significant contributions in CER in the U.S. and the United Kingdom, a comparative analysis of research between the two regions can identify strengths and opportunities for each.**

RESEARCH QUESTIONS. Our research questions for this study were: *When comparing using the CAPE framework, what similarities and differences across areas of study exist among research studies with student participants from the UK and the U.S.?*and *What similarities and differences exist in reporting of participant demographics between studies with student participants from the UK and the U.S.?*

METHODOLOGY. We conducted a systematic mapping review of K-12 CS education research publications (2019-2022). We used the Capacity, Access, Participation, and Experience (CAPE) framework to group publications that studies similar topic areas. We then ran descriptive statistics (counts and percentages across number of codes and also number of publications) to identify commonalities and differences between the regions with respect to areas of focus and student participant demographics.

FINDINGS AND IMPLICATIONS. Our results suggest that dominant-norming likely exists in our corpus of CER that needs mitigating. Studies with UK participants reported prior experience and gender of participants significantly more, while those in the US were twice as likely to report participant race/ethnicity significantly more. Research focused on pedagogy, the topics of student engagement, and content knowledge were studied more frequently than other areas in both regions. There is limited research related to funding for computing education, school-based extracurricular activities, and social-familial influences, all of which are critical for understanding their impacts on students.

Index Terms—**-12 CS education, systematic mapping review, equity-12 CS education, systematic mapping review, equityK**

I. Introduction

In recent years, the computing education research (CER) community has shifted its focus to a larger equity perspective in primary and secondary computing education (or K-12) (1). This shift has been driven by government as well as industry efforts that recognize a critical need for more employees capable of filling the numerous computing-related jobs that are expected to rise over the next decade. Further, as computing skills are needed to be properly trained for other types of jobs such as in education, healthcare, and even the fine arts, it is practical and necessary for schools to bring computing to their students. The focus, then, on ensuring CS education is impactful on all students is vital for the future of K-12 computing education. Historically, however, there has been a lack of emphasis on diversity in computing education in both the United States and the United Kingdom (2; 3; 4; 5).

Over the last two decades, researchers have raised awareness about the lack of access to and participation in CS education, as well as the inequitable outcomes of CS learning experiences across many groups of students (6; 7; 8). Awareness of these issues has risen internationally (9; 10), with many researchers and educators working to find practical and permanent solutions for teaching CS to all students. Since the field of CS education still remains relatively new, the importance of research remains high, and building a strong foundation for CER is critical so that promising practices for teaching CS can be identified and adapted.

Recognizing the need for strong foundations of CS ecosystems, Fletcher and Warner (11) designed the CAPE Framework (Figure 1) for establishing effective equitable education by examining it in terms of specific components. The CAPE framework's components consist of **Capacity** for schools to equitably offer CS education, to provide equitable **Access** to CS education, to provide equitable student **Participation** in CS education, and to provide student **Experiences** in CS education that lead to equitable outcomes (11). CAPE has also served as a disaggregation framework for understanding how to measure equitable outcomes of CS learning. CAPE supports equity-focused research due to its careful consideration of the many facets of the education ecosystem ensuring that all students are receiving impactful experiences in computing education.

The goal of our study was to identify commonalities and

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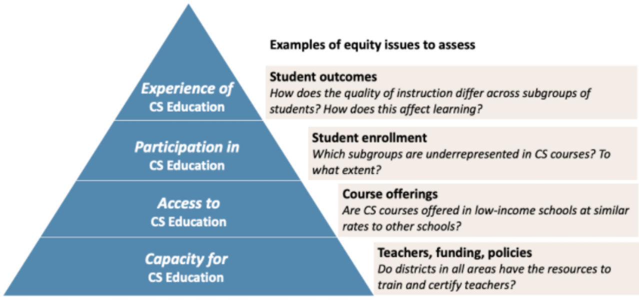

Fig. 1. CAPE Framework (12).

differences in K-12 CER conducted in the United Kingdom (UK) and the U.S. that were focused on gaps in meeting the needs of a variety of learners (13), including the backgrounds and identities of student participants (14). Our research questions were:

RQ1 *When comparing using the CAPE framework, what similarities and differences across areas of study exist among research studies with student participants from the UK and the U.S.?*

RQ2 *What similarities and differences exist in reporting of participant demographics between studies with student participants from the UK and the U.S.?*

This research study is important for identifying strengths and opportunities for growth across the two regions, including how researchers can learn from each other in growing the overall corpus of research on K-12 computing education.

II. Related Work

Contributions of comparative education researchers can provide insight into educational reform, improved teaching practices, descriptions of similarities and differences in education, and can even drive philanthropy (15). Education research has compared a variety of topics between the U.S. and the UK, including the educational ecosystem across the two regions focused on skill-specific education (16), overall education systems (17), and subject area implementation (18), including computer science (CS) (19).

A. Including All Students in Research

Every country and region of the world has various groups of marginalized students, though who comprises this may differ and research has shown that marginalized students' education outcomes can differ. For example, previous research indicates a correlation between students' family's socio-economic status and academic achievement (20; 21; 22; 23). When it comes to CS education, many questions remain unanswered in the search for equitable outcomes across all students learning CS. Considering inclusivity in this context as well as others can help broaden the CER corpus of literature.

Previous studies have indicated a number of areas in which the field of CER has room to grow when building a corpus of literature that encompasses all students, particularly those who are marginalized. Identified challenges include the need for explicitly stated research questions (24), explicit connections between findings and relevant theories (25; 26), details on the context of studies (including student demographics (27)), the reporting of statistical data in K-12 (28), and the use of evaluation instruments with evidence of reliability and validity for groups of student with varying backgrounds and characteristics (29). Further, some publications do not report participant characteristics (30) and consideration of intersectionality is often missing (6; 30). This can leave researchers and practitioners searching for prior work that considers outcomes of various students groups who may face greater challenges in their educational environments or home lives.

Dominant norming is a known and problematic issue in education research that occurs when students from majority population groups are included in studies, while students from marginalized groups are not (31). This leads to evidence that is largely skewed and favors students and cultures from the dominant groups and can disadvantage others. Further, when this data is *not* reported, it can also contribute to dominant norming and questions can also arise about whether the evidence from a non-reporting study has findings suitable for a particular population. For example, if all students in a study have had prior experience learning CS before starting an introductory course and this data is not reported, then it can lead to misleading results and adoption of a practice that may negatively impact students who do *not* have experience.

B. Regional Grounding

Within the United States, 14% of public school students received special education services under the Individuals with Disabilities Education Act (IDEA) (32), with approximately 1 in 3 receiving services for specific learning disabilities. Over the decade from 2010 to 2021, Hispanic representation in public schools surged from 23% to 28%, solidifying their presence as a growing student demographic. Meanwhile, the share of White students dipped from 52% to 45%, and Black student representation rose slightly from 15% to 16% (33). This growing diversity can lend itself to shaping race relations (34), even within education (35).

In the UK, inequality is part of the education ecosystem as well (36). Previous research suggests that inequalities in the education system disadvantage immigrants and ethnic minorities (37). Multiple research studies provide evidence that suggests that Black and minority ethnic (BME) students experience racism within schools (38), including racism that is more covert (in subtly nuanced ways) (39). Ethnic minority groups in the UK are also not as likely to be admitted to elite universities as their counterparts (40). These all point to how the UK also struggles with inequalities within the education system that must be acknowledged and addressed in computing education research (41). Similarly, there are many reports on the gender gap in learning computing in schools in the UK (42) and there is a need for additional research on students with disabilities and how they learn computing (43).

C. CAPE Framework

Existing mapping and gap analysis of K-12 CER have found there is room for higher quality and more quantity (6; 30; 44). These include analysis of the subjects of research studies (45) and reports on pre-college activities (27). **(author?)** found that most K-12 research is focused on programming language and environment or student engagement and motivation; equity was not mentioned as a lens for this review (46). Several reviews of the CER literature have identified reporting gaps that prevent high-quality synthesis and meta-analysis (47; 48; 49; 50). Analysis of the CER landscape, particularly in K-12, has yet to be thoroughly investigated through an equity lens, including gaps where more focus is needed. The CAPE Framework provides a way to disaggregate key components within CS education that considers all students. CAPE has been adopted in the U.S. and the UK by researchers carefully considering factors in each and how they may impact student learning outcomes.

III. Research Methods

A. Mapping Review

To answer our research questions, we first performed a systematic mapping review (51) of CER papers (2019-2022) using data from the publicly available K-12 Computing Education Research Resource Center dataset (52). We selected four years prior to when the analysis was conducted and to pilot the process of analyzing and coding the papers and finalizing the codes as we prepare to conduct further analysis of research articles from prior years.

While the process of developing the initial dataset is covered in thorough detail in (53), we provide a brief summary here to provide context. The dataset includes K-12 CER focused from the following venues that have significant K-12 computing education publications: ACM International Computing Education Research (ICER), ACM Innovation and Technology in Computer Science Education (ITiCSE), ACM SIGCSE Technical Symposium on Computer Science Education (SIGCSE TS), ACM Transactions on Computing Education (ToCE), IEEE Frontiers in Education (FIE), IEEE Global Engineering Education Conference (EduCon), IEEE Research in Equity and Sustained Participation in Engineering, Computing, and Technology (RESPECT), IEEE Transactions on Education (ToE), Journal of Educational Computing Research (JECR), Koli Calling (Koli), Taylor & Francis Computer Science Education (CSE), and Workshop in Primary and Secondary Computing Education (WIPSCE). Publications included in the mapping review satisfied the following inclusion criteria: described or evaluated a computing activity or process, targeted K-12 educational ecosystem (specifically or more broadly), and designed to teach computing or computational thinking (54).

We adapted the PALSAR methodology (51; 55), a set of steps to define protocol (inclusion/exclusion criteria, scope and dataset), search for studies that meet the criteria, appraise the quality of the dataset, synthesis the data and conduct analysis, analyze results, and report on research findings.

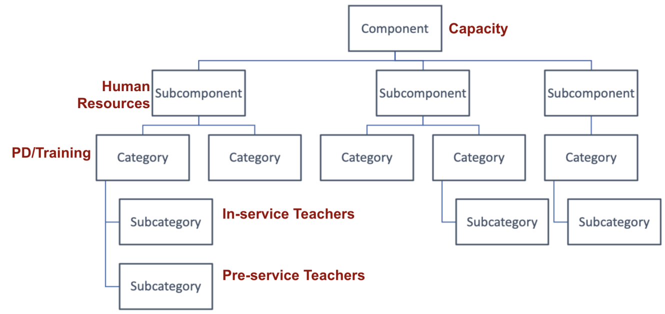

Fig. 2. Hierarchy of codes. Codes are the subcategories.

Using this process, our final dataset for our analysis consisted of 340 distinct publications that were research studies (i.e., not experience reports or position papers). To define the factors studied in each publication, we established codes *a priori* from previous research and categorized each into one of the CAPE components. During review, when factors were found that were not in the codebook, they were added. To ensure the rigor of our mapping review, we followed the Framework Method during the coding process (56), establishing norm-setting where four researchers coded the first two publications together. The researchers then coded 16 publications, with two researchers coding each. After independent coding, the four researchers discussed anomalies among the codes of the 16 publications until a consensus was reached on each publication. The previous two phases were repeated with two researchers until all coding was complete. By using this process, inter-rater reliability was not needed since all codes were reconciled. This process resulted in the formation of subcomponents (Figure 2) for each component (53).

B. RQ1 and RQ2 Data Analysis

To answer our research questions, we conducted descriptive statistical analysis for publications with student participants in the UK and in the U.S. The total number of publications and CAPE codes by region is shown in Table I.

For research question 1, percentages were calculated by region by dividing the total number of codes per subcomponent by the total number of codes placed for *publications*. For example, to calculate the percentage of codes for the **Capacity** subcomponent *Pedagogy* for publications with participants in the UK, we calculated the percentage from the number of subcomponent codes (19) against the total number of codes for publications in the UK (98). We also conducted Chi square tests and a Fisher's exact test across the two groups to test whether the distributions were similar (57) within each component.

It is important to note that for all publications included in this study, multiple CAPE codes are applicable. Within each CAPE subcomponent there are categories and subcategories that further identify research being conducted in these areas. All publications were coded at the subcategory level for in-depth analysis. Therefore, it is possible for a publication to have similar codes of the same subcomponent or even CAPE component. This results in the counts and percentages of codes **manually tagged during analysis** for each associated subcomponent (Table II) to vary from the number of **publications** associated with each subcomponent (Table III).

For research question 2, we recognize that not all research studies include students as participants. The data provided in the dataset reflects this by indicating whether the demographic data was specified, unspecified, or not applicable. We excluded papers where students were not included in the study (not applicable).

	# Papers	# Codes	# Distinct Codes
UK	14	98	80
U.S.	118	724	146
Total	128*	815*	150*

TABLE I: Total number of papers and codes, and number of distinct codes. (*Four publications were excluded since the studies included student participants from both the UK and the U.S.)

C. Positionality Statements

The researchers undertaking this work are experienced researchers with a deep understanding of the K-12 CS education ecosystem. The researchers bring with them an equity-focused lens and apply it to this work. This has resulted in sharing various factors that can influence building an education program that meets the needs of all students. These factors were examined in light of existing literature to determine the appropriate codes for each publication. For the quantitative data analysis, one researcher conducted the majority of the descriptive analysis and another researcher conducted the two sample Chi-square goodness-of-fit test.

IV. RESULTS

A. RQ1: Topics Investigated

To address **RQ1**: *When comparing using the CAPE framework, what similarities and differences across areas of study exist among research studies with student participants from the UK and the U.S.?*, we compared the number of codes for each subcomponent by student participant location (UK or U.S.). Table II presents the counts and percentages of codes listed for each component and each subcomponent created during the systematic mapping review.

What stands out in Table II are the similarities between the two regions when assessing for subcomponents with few or no publications in these areas. For Capacity subcomponents Community Environment, Culture, & Ideology (CEC & I) (0%, 1%), *Funding* (0%, 0%), Policies (3%, 1%), and Standards (0%, 1%), there seems to be a limited number of investigations in both regions. Similarly, we found no to few investigations focused on **Access** subcomponents Community-based activities (0%, 0%) and School-based Extracurricular activities (1%, 0%). For **Participation**, both regions have a small number of investigations compared to the other subcomponents in the framework. Finally, Learning Strategies (3%, 2%) and Social-Familial Influences (0%, 1%) are Experience subcomponents that have no to a small number of investigations for both regions.

There are also subcomponents with a similar higher percentage of publications between the two regions. Capacity subcomponents *Curriculum* (14%, 8%) and *Pedagogy* (19%, 18%) and Experience subcomponents *Content Knowledge* (12%, 12%) and *Student Engagement* (29%, 29%) have similarly large numbers of codes from each region. From Table II, it can also be seen that there are subcomponents where the number of codes differ., such as the Capacity subcomponent *School Environment, Culture, & Inclusion (SEC&I)* (3%, 13 %).

To compare the U.S. and UK distributions across subcomponents of each component, we conducted Fisher's exact test, which is a form of Chi-square test used when some cell values are low or zero (as is the case in Table II). For Capacity, Fisher's test indicated there is an association between region (i.e., U.S. vs. UK) and subcomponent studied (Fisher's exact p ¡ .001). It appears that studies focused on participants in the U.S. more often focused on the Capacity subcomponent School Environment, Culture, & Ideology compared to publications with UK participants. However, such an association was not shown among the subcomponents in any of the other components (Access, Participation, or Experience). To summarize, while there are some variation between the U.S. and UK within each subcomponent, the two distributions do not significantly differ for the Access, Participation, or Experience components.

We also compared the *number of publications* for each subcomponent by student participation location. Table III presents the counts and percentages of publications associated with each component and subcomponent from the codebook used during the systematic mapping review.

What stands out in Table III are the similar patterns that emerged in Table II when analyzing the number of publications associated with each code compared to the number of codes themselves. Throughout the Access, Participation, and Experience components, similar percentage ratios were expressed in Table II. Additionally, in the Capacity component, for subcomponent with no to little investigations, those results still hold in Table III.

B. RQ2: Student Participant Demographics

To address **RQ2**: *What similarities and differences exist in reporting of participant demographics between studies with student participants from the UK and the U.S.?*, we analyzed publications that included student participants from the UK and the U.S. to determine the frequency of reporting of participants' gender, race, socioeconomic status (SES), disability, and prior CS learning experience. Since reporting participant demographics was not applicable in some studies, these were excluded from our analysis. Total number of publications included for UK included gender, race, SES, and prior CS experience, each at $n = 14$, and disability ($n = 13$). For the

		UK		U.S.	
Component	**Subcomponent**	**Count**	**%**	**Count**	**%**
Capacity	Community Environment, Culture, & Ideology	0	0%	4	1%
	Curriculum	14	14%	58	8%
	Funding	0	0%	1	0%
	Human Resources	2	2%	37	5%
	Pedagogy	19	19%	132	18%
	Policies	3	3%	6	1%
	School Environment, Culture, & Ideology	3	3%	93	13%
	Standards	0	0%	6	1%
Access	Community-based Activities	0	0%	1	0%
	Curriculum Offerings	4	4%	37	5%
	School-based Extracurricular Activities	1	1%	0	0%
Participation	Community-based Activities	2	2%	13	2%
	Course Enrollment	0	0%	15	2%
	School-based Extracurricular Activities	1	1%	2	0%
Experience	Content Knowledge	12	12%	90	12%
	Learning Strategies	3	3%	16	2%
	Social-Familial Influences	0	0%	5	1%
	Student Engagement	28	29%	208	29%
Total		98		724	

TABLE II: Count and percentage comparison between UK and U.S. CER CAPE component and subcomponent codes. This table displays areas where a lack of research (Funding, Standards, etc.) occurs in research papers in the UK and U.S. Additionally, from this table is it clear areas that have had a majority of attention in the research corpus, such as Pedagogy and Student Engagement.

		UK		U.S.	
Component	**Subcomponent**	**Count**	**%**	**Count**	**%**
Capacity	Community Environment, Culture, & Ideology	0	0%	4	3%
	Curriculum	4	29%	49	42%
	Funding	0	0%	1	¡ 1%
	Human Resources	2	14%	28	24%
	Pedagogy	7	50%	68	58%
	Policies	3	3%	6	5%
	School Environment, Culture, & Ideology	5	36%	51	43%
	Standards	0	0%	4	3%
Access	Community-based Activities	0	0%	1	¡ 1%
	Curriculum Offerings	2	14%	25	21%
	School-based Extracurricular Activities	1	7%	0	0%
Participation	Community-based Activities	2	14%	13	11%
	Course Enrollment	0	0%	9	8%
	School-based Extracurricular Activities	1	1%	2	2%
Experience	Content Knowledge	5	36%	48	39%
	Learning Strategies	2	14%	16	14%
	Social-Familial Influences	0	0%	4	3%
	Student Engagement	9	64%	71	60%
Total		14		118	

TABLE III: Count and percentage comparison between UK and U.S. CER publications. From this table we can see similar patterns between Table II and Table III.

U.S., gender ($n = 98$), race ($n = 98$), SES ($n = 97$), disability ($n = 90$), and prior CS experience ($n = 95$).

As shown in Figure 3, gender was the most reported student participant demographic in both UK (71%) and U.S. (62%) publications, though gender is reported more in the UK For race, the difference is even wider. While 57% of the publications reported race/ethnicity of student participants located in the U.S., only 21% reported student participant race/ethnicity in the UK .

Few publications with student participants included data about the socio-economic status of the families of the student participants' in UK (29%) and U.S. (30%) studies. These are both, however, well below reporting for even half of the papers. A striking result is the lack of reporting in studies with student participants that reported participant disabilities in both the UK (0%) and the U.S. (3%). Finally, the participants prior experience in CS was reported in half of publications that reported on student participants in the UK (50%), while only under a third of the U.S. publications (33%) reported the same demographic.

To compare the U.S. and UK percentages of reporting student participant demographics, we conducted a Chi-square test for the demographics: gender, race, socio-economic status, and prior experience and a Fishers Exact Test for disability because of a zero-value. For gender, socio-economic status, disability, and prior experience the Chi-square and Fishers Exacts tests indicated there is not an association between region (i.e., U.S. vs. UK) and demographic reported (gender: $X^2(1, N = 112) = 2.1, p > .15$ socio-economic status: $X^2(1, N = 111) = .01, p > .9)$ disability: (two-tailed $p = 1$) and prior experience: $X^2(1, N = 109) = 1.6, p > .2)$). The test indicated there is an association between region and demographic reported for race/ethnicity ($X^2(1, N = 112) = 6.3, p < .01)$.

V. Discussion

One of the most notable findings is the need for additional education research across multiple areas of capacity, access, participation, and experience. For example, very few studies investigate social-familial influences on students' learning outcomes or even experiences of students engaging in learning strategies. This highlights a need for additional education research across K-12 computing education.

Below, we consider the findings according to the research questions.

A. RQ1: Topics Investigated

In general, we found that publications that included either UK or U.S. student participants had both similarities and differences across the CAPE components, though the distribution was mostly similar. The Capacity subcomponents *Pedagogy*, *Curriculum*, and *School Environment, Culture, & Ideology* were more frequently studied than others in both regions. This could reflect the importance of these topics in teaching students and the immediate necessity of what and how to teach

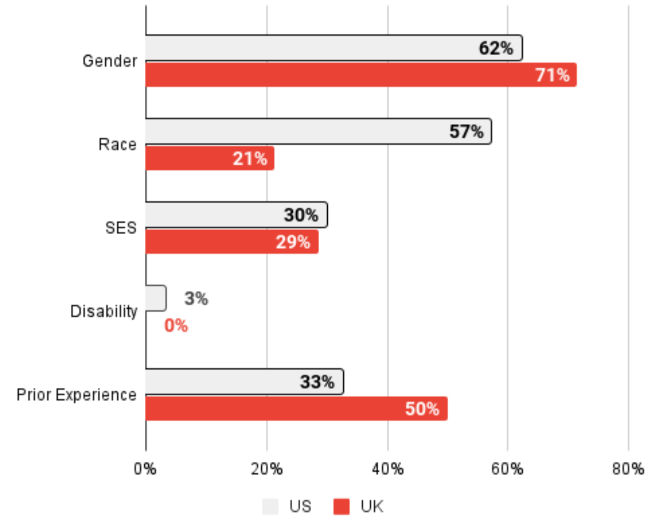

Fig. 3. Publications reporting gender, race, SES, disability, or prior CS experience of student participants.

computing. We note here that publications that included student participants in the U.S. were more likely to study *School Environment, Culture, & Ideology* more than those in UK. This is interesting and worth more investigation since studies have previously shown how leadership of principals (U.S.) and headmasters (UK) correlates with academic achievement (58; 59) and other research supports the correlation between school environment and academic achievement.

Capacity had a number of subcomponents that were only lightly investigated: *Community Environment, Culture, & Ideology* as well as *Policies*, *Standards*, and *Funding*. Similar to school environment, there is a rich set of research that provides a correlation between *Funding* and academic outcomes (60; 61) in both regions. Further, within the field of computing, it is well-known that a barrier to using physical devices to teach computing, like robots, prevent a barrier for schools that lack *Funding* (62). This appears to be an area ripe for further investigation in both regions.

The Experience subcomponent *Social-Familial Influences*, was also only lightly investigated, suggesting that more work is needed to better understand how family structures support learners' experiences with computing. This is particularly important, as previous research has shown that social-familial influences impact student achievement in general (22; 63) and in CS in particular (64; 65; 66). The most striking observation that emerged from the analysis was the low number of publications in the **Access** and **Participation** components. These gaps are worth highlighting, because they comprise critical steps in the pathways to build CS education with equitable outcomes (67). This may in part be because researchers are not aware their importance or due to other challenges in conducting research or collecting data in these areas. However, for the CER community to have a comprehensive understanding of equity in K-12 CS education, it is imperative to report them.

B. RQ2: Student Participant Demographics

We sought to find the commonalities and differences in reporting of student participant demographics across the two regions. Studies with student participants in the U.S. report their race and socio-economic backgrounds significantly more than those in the UK. Publications focused on UK student participants were much more likely to report prior experience and, to a lesser extent, gender. Prior experience is particularly key as it is known to be correlated with student self-efficacy and retention (68).

However, there is significant room for further reporting by researchers within both regions. In contrast, studies with participants located in the UK reported their participants' prior experience significantly more. Prior experience has been shown to be a key factor in student learning outcomes for computing (69) and thus ought be considered in studies where outcomes of various students are considered.

Seven out of ten publications reporting student participants from UK reported their gender, while those with student participants in the U.S. reported race significantly more. While students from marginalized racial and ethnic groups are been shown to encounter forms of racism in education and with less than equal outcomes to their peers within both regions (41; 70), the issue appears to be more frequently raised within the U.S. This might be due to the publicly raised disparities driven by racial differences that have led to systemic barriers for those from marginalized groups.

The most significant aspect of the results was the need for both regions to report key demographics of study participants. This highlights the ongoing need for improved reporting of demographics in the CER community (27; 50). While we do not advocate that each study must be inclusive of all types of students, it is well worth noting that when looking at the CER literature in aggregate, if this data is not reported, we risk identifying promising practices in CS education that are *dominant-group norming* (31), which is highly problematic in education research and only serves to perpetuate inequities within any region where a study is conducted.

Overall, the lack of reporting demographic data is a challenge in the CER community. Reporting participant demographics does not imply that equity is a focus of the published work. However, reporting these measures is an important start to contextualizing K-12 CER, and CER more broadly. It further provides better data for conducting meta-synthesis as well as understanding the context of the particular study, including whether or not equitable outcomes have been achieved.

C. Limitations

The results reported in our mapping review are limited by the inclusion criteria for the published works examined. We only studied the four most recent years of CER publications to provide an appropriate landscape of the field. Many of the studies in these publications took place at the height of the COVID-19 pandemic. This may have caused challenges with the research questions the authors were able to investigate; thus, reducing the number of publications in certain subcomponents within the CAPE Framework.

While we used the Framework Method (56) where two people identified the appropriate codes for each publication during the mapping review, other researchers may have coded the publications differently. Our codes may also differ from how authors would have coded their own work. The same concerns are appropriate for the equity measures dataset that we utilized from the K-12 CS Education Research Resource Center (52). We also do not know if intersectionality was considered for publications that reported equity measures investigated in this paper. Just because equity measures are reported for a publication, does not mean they were considered in the context of what the publication was investigating.

Finally, we did not correlate findings from research question 1 to research question 2. Exploring how various student groups are included in various types of studies could shed additional light on research needs as we work to build a strong foundation of computing education research for decades to come.

VI. Conclusion

While the results of the focus areas studied have overall similar distributions, this study surfaces issues important to both regions that remain underinvestigated that have prior evidence of their relationship to student outcomes. The findings on demographic data collected from studies in both regions suggest a need to mitigate dominant norming of the results of our collective studies, suggesting that we are not collective producing studies that are designed to meet the need of all students learning computing. As members of the computing education research community, it is incumbent upon ourselves to ask how we can better collect and report data, as well as integrate this data in our research, to ensure that this insidious problem that leads to outcomes that disadvantaged certain students can be mitigated.

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