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High School Computing Education: The Landscape of Equity-Enabling Research (Fundamental)

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Abstract

Motivation: Demographic disparities in computing instruction contribute to a tech workforce and a society where the ever-increasing role of computing reflects those disparities. One facet of the solution is to broaden the computing education research corpus to include experiences of all students, particularly those from marginalized groups, and to adopt best practices for high-quality research.

Research Question: What gaps related to participants in computing education research studies exist? How might these contribute to the lack of equity in high school computing?

Methodology: Using a curated data set of research articles focused on K-12 computing education, we analyzed articles that included high school students as study participants ($n = 231$) to determine which dimensions of high quality and/or equity-enabling research were included.

Results: The yearly growth rate for studies of high school computing averaged over 40% during the past decade. While that research has some indicators of being increasingly focused on equity, there are also substantial gaps. For example, while publications that include student disability status have been increasing, the number still remains very low (fewer than 5%). And while most studies adhere to the practices of high quality research (e.g., specifying a research question), there is some room for improvement.

Implications: Awareness of the landscape of recent computing education research that focuses on high school students will enable education researchers to align their efforts with the needs of all students, including those who are less likely to study computing.

1 Introduction and Background

Under-representation by race [1] and gender [2, 3] in computing is by now a well-known problem in computing education research. Similar disparities exist for students with disabilities [4] and those living in rural areas [5]. Barriers to accessing computing instruction constitute not only a moral issue but also can lead to computing technologies that promote inequities in arenas ranging from the criminal justice [6] to the health care [7] systems. Further, companies that lack diversity experience worse performance [8].

One facet of rectifying these problems is the development of a corpus of education research that studies the experiences of all students, not just those who come from groups that have traditionally studied computing. A constant implementation of these practices can contribute to curriculum and pedagogy that is more effective for dominant groups being integrated into educational systems, thereby placing students from non-dominant groups (often marginalized or excluded) at a disadvantage [9]. Further, historically, computing education research has not often specified demographic information about study participants [10], making it difficult to determine how and whether findings apply to all student groups. More explicitly, by not specifying when all participants in a study are White, "Whiteness" becomes invisible, which by default then secures the *norm of Whiteness* [11, 12].

Prior analysis of the demographics of computing education research study participants has used an approach of critical demography [13] in order to explore norms in the literature. This work found that most studies did not provide information on *how* demographic data was collected and frequently used categories and response options that were suboptimal for fair representation (e.g., aggregate terms, gender binaries) and that most computing education research focused on post-secondary students. Analysis of K-12 computing education research found that boys and students in the US are most likely to be study participants and that race and socioeconomic status are not often reported [14], but little to no previous research has focused specifically on the landscape of high school computing.

As computing education expands in K-8, analysis focused specifically on high school becomes increasingly important since a more granular perspective is key to better understanding the research base and its gaps for secondary students. The historical trajectory of computing education has been one of expansion from the most advanced levels of education (i.e., graduate school) to the most basic, the elementary grades [15]. In the middle of that span are high school students, whose computing instruction has some overlap with both primary and tertiary education but is also distinct from those age groups. Hence, this study explores the research question: What gaps related to participants in computing education research studies exist? How might these contribute to the lack of equity in high school computing?

2 Methodology

The K-12 Computing Education Research Resource Center vets and then curates relevant articles from over a dozen venues (see Table 1) that publish computing education research, including dedicated journals and conference proceedings; there is also a mechanism for submissions to the resource center by authors. The inclusion criteria require that articles (1) describe or assess a computing activity, (2) focus on K-12 students and/or their instructors, and (3) focus on an activity whose goal is teaching a computing or computational thinking concept.

Title
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)
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)
Workshop in Primary and Secondary Computing Education (WIPSCE)

Table 1: Research Study Sources

Each abstract from the set of venues is reviewed to determine whether it meets the inclusion criteria. Then, data for over 40 variables are logged for each included article; this data is verified by a second reviewer [16]. Those variables include whether the grade level of study participants is specified and, if so, which grade levels are included. There are over 1,200 articles in the resource center that were published between 2013 and 2022 (inclusive), 771 of which were research studies (i.e., not experience reports or position papers).

Of those, 472 specified the grade level(s) of study participants, and 231 of those included high school students (grades 9 through 12, roughly ages 14 through 18). Figure 1 shows the count of research articles that included high school students each year as a percentage of the articles where the grade level of student participants was specified. We analyzed this set of 231 articles in order to determine which factors of high-quality and/or equity-enabling research were included. Research that is equity-enabling is defined as research that enables impactful education that leads to equitable outcomes [17].

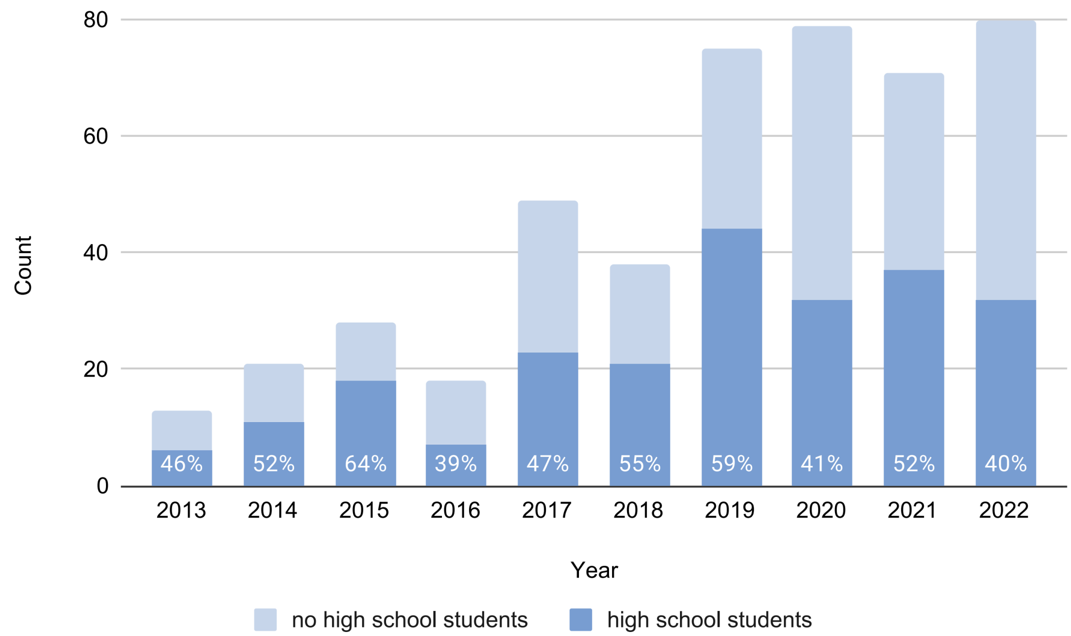

Figure 1: Papers focusing on high school students as a percentage of all papers that specified grade level

3 Results

3.1 Metadata

As Figure 2 shows, there is a substantive increase in the number of studies each year, and an even greater increase in the number of unique authors per year.

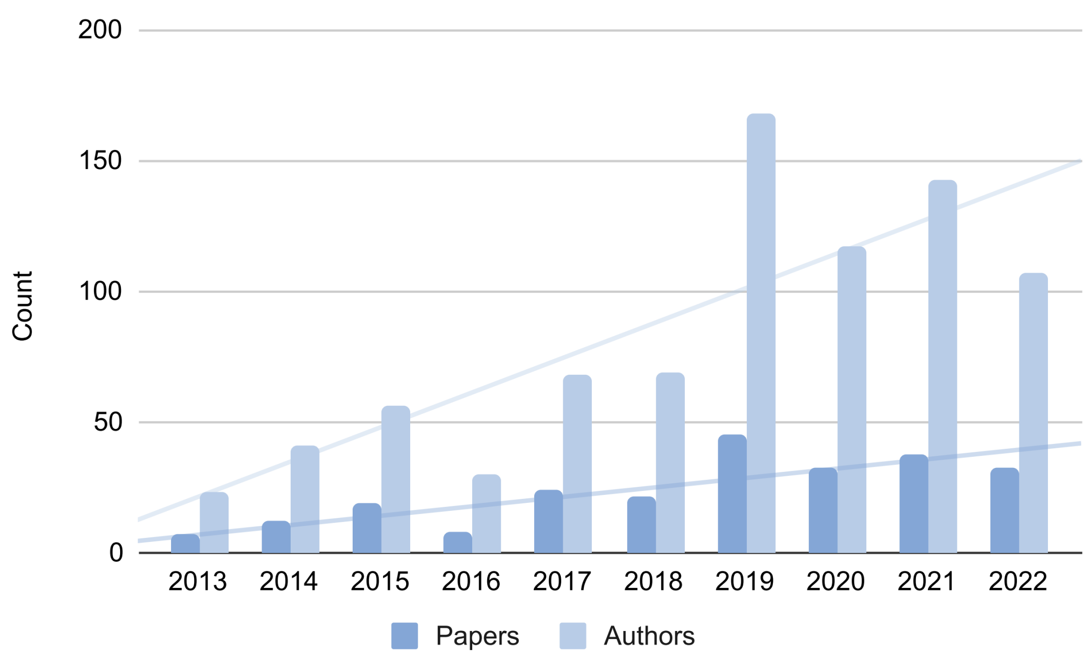

Figure 2: Count of papers and authors by year

Table 2 shows the paper count for the 9 venues with the most articles related to high school computing education. The top two venues, the Association of Computing Machinery (ACM) SIGCSE Technical Symposium and IEEE Frontiers in Education (FIE) conference proceedings, together account for over a third (37%) of high school computing education studies.

Venue	**Count**
SIGCSE Technical Symposium on Computer Science Education	58
Frontiers in Education (FIE)	28
Innovation and Technology in Computer Science Education	25
Transactions on Computing Education	21
Computer Science Education	16
International Computing Education Research	15
Koli Calling	15
Research in Equity and Sustained Participation in Engineering, Computing, and Technology	14
Workshop in Primary and Secondary Computing Education	12

Table 2: Venues

Organization	**Count**
North Carolina State University	13
The University of Adelaide	9
Georgia Institute of Technology	8
The Findings Group	6
UCLA	6
University of Washington	6

Table 3: Organizations

There are 281 different institutional affiliations in the data set; Table 3 shows the organizations listed as affiliations in more than 5 papers. Five out of six of these organizations are located in the US; all are in English-speaking, higher-income countries.

3.2 Themes

Three variables in the data set are used to explore the themes of high school computing education studies: the study's area of focus, its keywords, and its citation count.

Each article in the data set is assigned a focus area. Figure 3 shows the proportion of papers that have each focus area over time (the legend indicates the total number of articles with each focus area). Some focus areas, such as resources (e.g., a tool), show substantive variability from year to year and no clear trend. Other areas have a trend, such as student activity (which decreases over time) and studies focused on the learner (which increase).

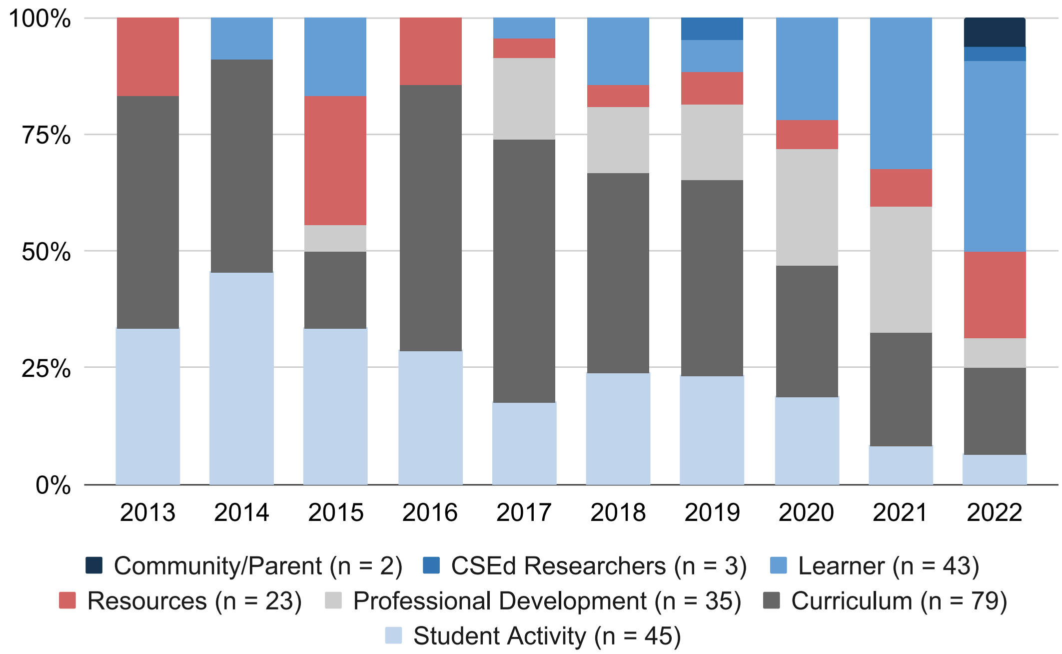

Figure 3: Focus area by year

In this dataset, 82% of articles had keywords, with a total of 600 different keywords (synonymous keywords, such as *K-8 education* and *K-8*, were combined for this analysis). Of those 600 keywords, 12 occurred in more than 4 years. A scaled count for each keyword was calculated for each year by dividing the raw count of papers with the keyword by the number of papers with keywords and multiplying the result by 1,000 (for readability).

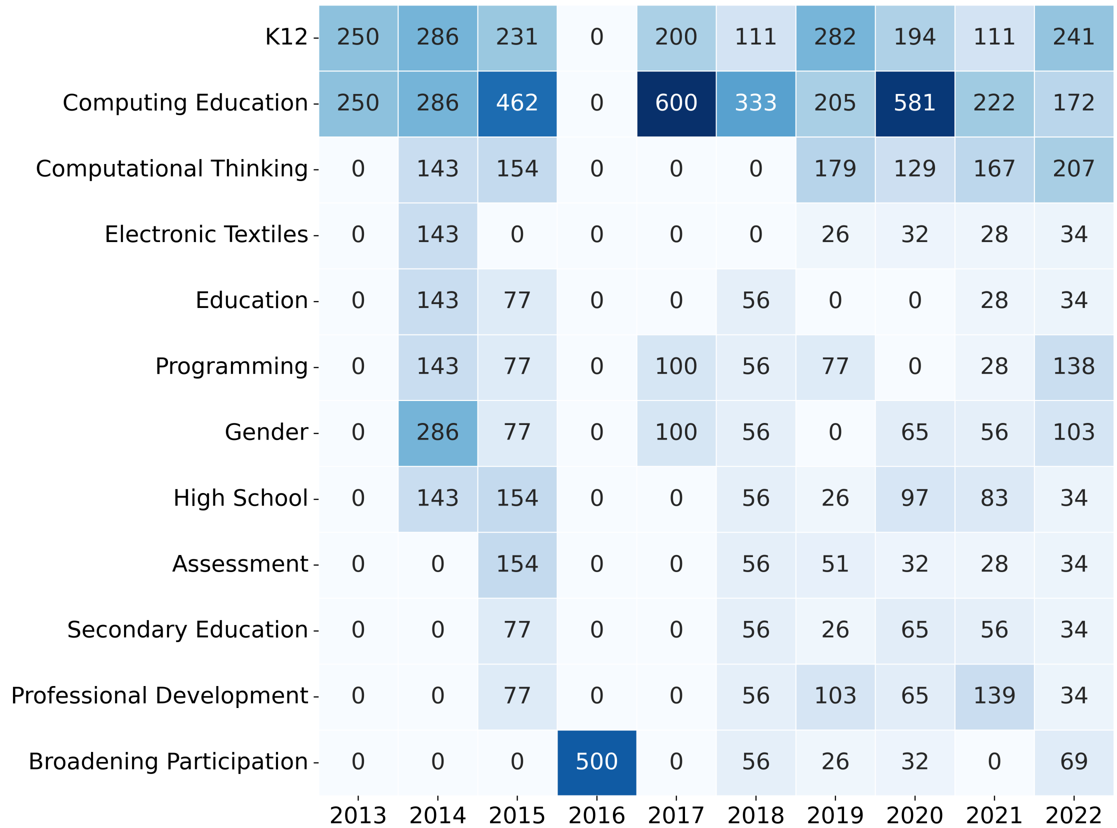

Figure 4: Scaled frequency of keywords occurring in at least 4 years

As Figure 4 shows, unsurprisingly, *K-12* and *computing education* are consistently common keywords. The year 2016 appears as an outlier: the preponderance of references to *broadening participation* stems from the low number (7) of studies meeting the inclusion criteria for that year, only two of which had keywords. The keywords occurring in more than 10 articles are *computing education* (59 instances), *K-12* (37), *computational thinking* (26), *equity* (13), *professional development* (13), *gender* (12), *programming* (12), and *high school* (12).

A scaled citation count was determined for each study by dividing its number of citations in CrossRef [18] by the number of years since its publication (in a few instances where CrossRef did not have data for a study, Google Scholar's citation count was used; one research report in the data set lacked entries in both CrossRef and Google Scholar and was imputed a citation count of 0). The most cited studies are shown in Table 4.

Title	Scaled Count
Gender stereotypes about interests start early and cause gender disparities in computer science and engineering	38.0
Computing whether she belongs: Stereotypes undermine girls' interest and sense of belonging in computer science	36.3
A crafts-oriented approach to computing in high school	17.6
From Scratch to "real" programming	15.4
Using commutative assessments to compare conceptual understanding in blocks-based and text-based programs	13.7
Exploring the effectiveness and moderators of block-based visual programming on student learning: A meta-analysis	13.0
Applying a transformative justice approach to encourage the participation of Black and Latina girls in computing	13.0
Pedagogy that supports computer science for all	12.3
Block-based versus text-based programming environments on novice student learning outcomes: A meta-analysis study	11.7
Does computer game design and programming benefit children? A meta-synthesis of research	10.7

Table 4: Most cited studies (scaled by year).

3.3 Research Approach

Table 5 shows the percent of studies including various research details; at least 8 out of 10 studies include key information such as a research question, which concepts were taught, how data was measured, and the count of participants.

Specification	Percent
Research question	86%
Which concepts taught	83%
How data was measured	99%
Participant count	84%

Table 5: Percent of studies including various research details

Figure 5 shows the measurement tools used most commonly in the data set: surveys are most common and are nearly twice as frequently used as interviews, which are the next most common measurement technique. (See the discussion regarding possible equity implications of these design choices.)

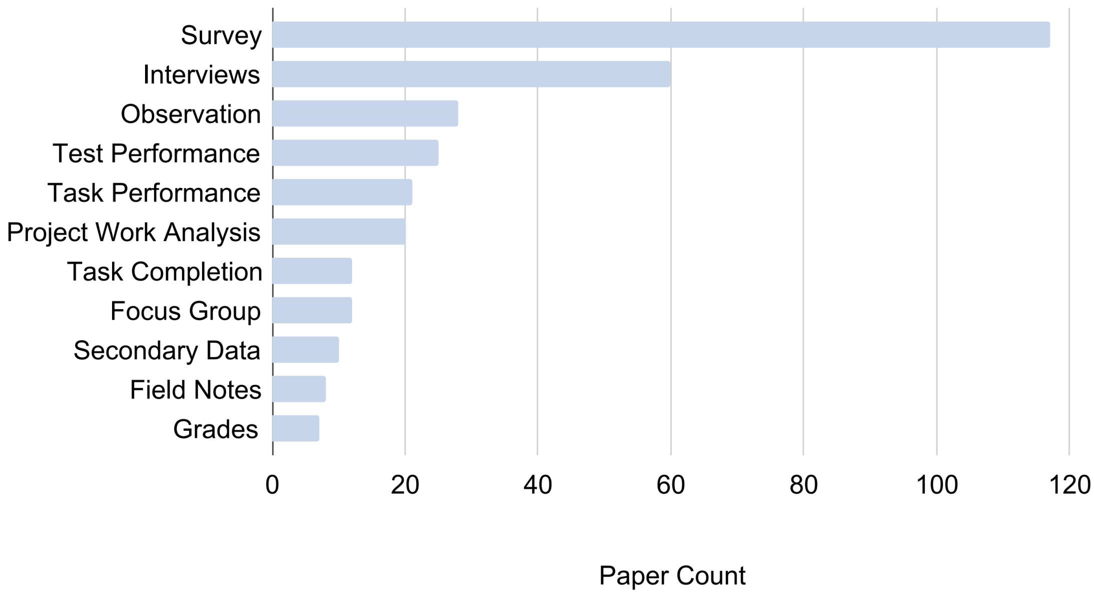

Figure 5: Most commonly used measurement tools

Fewer than half (40%) of studies involving a student activity specified whether that activity was required or optional. Of those studies that specified, elective activities were most common (74%).

As Figure 6 shows, Scratch is the most commonly used language or tool, with Python a close second.

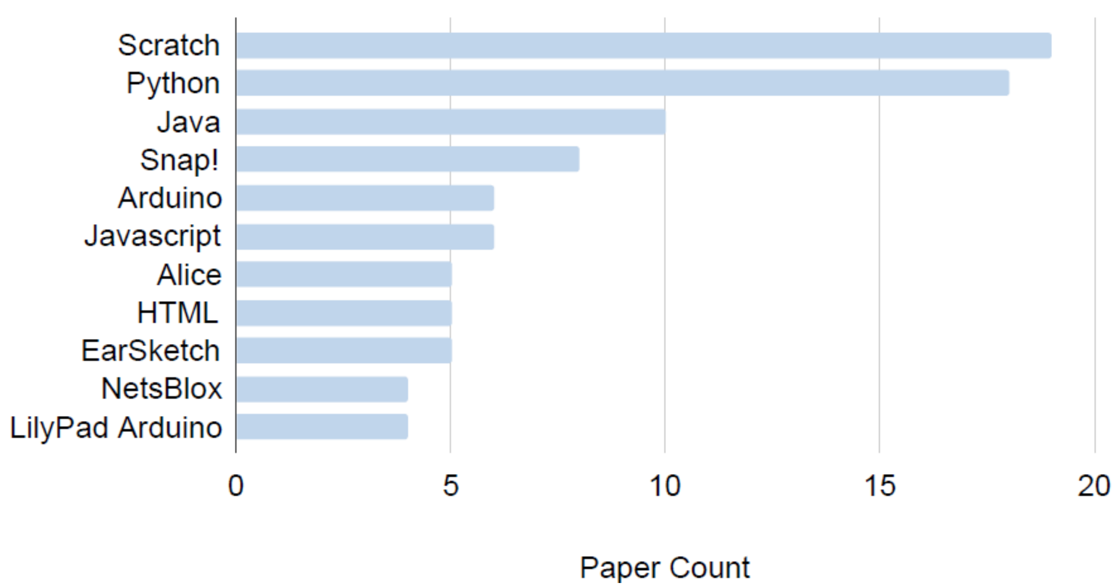

Figure 6: Most commonly used programming languages or tools

3.4 Equity-Related Factors

Tables 6 and 7 show paper counts by the country and by the US state of student participants, in raw and scaled counts. The scaled counts adjust the raw counts relative to the location's student population using World Bank [19, 20] or NCES [21] data; scaled counts were only generated for countries with more than 4 papers and states with more than 2 papers. Table 6 shows that, for both raw and scaled counts, research papers disproportionately include student participants from western, educated, and/or English-speaking countries. For those papers specifying a US state for the location of student participants, the same six states appear at the top of both lists, albeit with their order shuffled.

Raw Count		**Scaled Count**	
Country	**Count**	**Country**	**Count**
US	77	Finland	5.6
UK	13	Sweden	2.8
Germany	10	US	1.5
Brazil	9	Australia	1.2
Australia	6	UK	1.2
Finland	5	Germany	1.0
Sweden	5	Brazil	0.2

Table 6: Raw and scaled paper counts by country

Raw Count		**Scaled Count**	
State	**Count**	**State**	**Count**
Illinois	6	Illinois	3.1
California	6	Washington	2.6
New York	4	North Carolina	1.9
North Carolina	3	New York	1.5
Texas	3	California	1.0
Washington	3	Texas	0.5

Table 7: Raw and scaled paper counts by US state

Table 8 shows the percentage of papers that specify participant factors such as student socioeconomic status or instructor gender. With the exceptions of participant location and student gender, no factor is specified in more than half of the papers. Disability status is specified in very few (3%) papers; similarly, instructor race or ethnicity is specified in fewer than 1 in 10 papers. Most of these factors are increasingly likely to be specified over the time period of this study, with the exceptions of student race, ELL status, and location.

For papers that do specify participant race, White and Latino/a/x/e are the most likely groups to be mentioned (9 papers each), followed by Black or African American (8 papers), Asian/Pacific Islander (6 papers), and American Indian or Alaska Native (4 papers); note that papers may mention more than one group. Papers that specify gender mentioned girls/women (41 papers) and/or boys/men (37 papers); there were no references to gender beyond this binary.

Factor	Percent	Trend
Student Socioeconomic Status	14%	↗
Student Disability	3%	↗
Student Gender	65%	↗
Student Race	36%	↘
Student Ethnicity	25%	↗
Student English Learner Status	16%	↘
Student Prior Computing Experience	33%	↗
Student Location	69%	↘
Instructor Gender	26%	↗
Instructor Prior Computing Experience	35%	↗
Instructor Race	7%	↗
Instructor Ethnicity	3%	↗

Table 8: Percent specified and trend over time for study participant factors

4 Discussion

The field of high school computing education research is rapidly expanding, with most years in the study period showing substantive increases in relevant published studies, although there is some year-to-year volatility. That only six papers met the inclusion criteria in 2013 but 32 did in 2022 speaks to the expansion of the field.

4.1 Gender

Gender appears to be a key concern of high school computing education research. This finding is supported by several lines of evidence: *gender* is one of the few keywords to occur in more than a handful of articles, it is the concern of the two most commonly cited studies in the data set, and it is the only equity-related factor (other than student location) to be specified in more than half of the studies. However, despite this emphasis on gender, there are still substantive gaps in studying the impact of gender on high school computing students: over 2% of Generation Z (born 1997 - 2003) identify as transgender [22], but no studies in the data set involved categories for gender other than the traditional binary of girls/women and boys/men. Further, an examination of the most cited studies suggests that gender is more likely to be explored in relation to affective factors (e.g., the impact of stereotypes) than in relation to, for example, curriculum or activities. Given that some research shows gender differences in these areas [23–25], further research is warranted.

4.2 Location

High school computing education is under-researched, particularly as it pertains to student location. For example, Brazil is one of the most studied countries in the data set, making the list of the top countries for both raw and scaled paper counts. But there are only nine papers in the data set that involve student participants in Brazil. They cover a variety of topics, including computational thinking, female students' perceptions, and robotics. But no set of just nine articles can exhaustively analyze the needs of high school aged students in an entire country, especially one as large as Brazil; none of these studies focus on, for example, cybersecurity, accessibility, or hardware. And Brazil is the only South American country on either list of most common countries. Thus, this analysis suggests that, despite its rapid growth, much more computing education research is required to better understand the needs of high school students. Further, the paucity of research can make it difficult to analyze the research base, as is evident from the fact that the existence of only two relevant 2016 articles with keywords skews the keyword analysis for that year, as described above.

Underrepresentation by geographic location is also manifested in author affiliations: the most prolific organizations in the data set are in higher-income, Western, English-speaking countries, predominately the US. The extent to which research conducted in these countries is applicable globally is an open question, especially given the different contexts and educational systems found worldwide. Nonetheless, the rapid growth over the previous decade suggests that the field is at something of an inflection point, where decisions about whether and how to focus on equity concerns will have a magnified impact in the future. The movement toward expanding computer science instruction (including, in some areas, as a required subject) suggests the importance of current research and its trends.

4.3 Authorship and Venues

The fact that the number of authors is increasing much more rapidly than the number of papers suggests something of a shift in how computing education research is conducted: larger teams have the potential to include more diverse voices and thus may signal more equity-enabling research *if* these larger teams are in fact more representative of the student population and more attuned to equity-related concerns. Whether this is actually the case remains an open question, although previous research has observed an absence of diversity in computing education research [26].

Despite this growth in the field, only two venues included in the data set – SIGCSE TS and IEEE FIE – account for over a third of studies in the data set. This concentration highlights the importance of ensuring that these conferences foreground equity at every turn (e.g., in selection of committee members, in submission policies, in reviewer protocols) given their outsized role in the direction of computing education.

4.4 Disability

Participant disability is another category that is rarely studied, with only 3% of articles in the data set specifying student disability; by contrast, in the United States, about 15% of students receive services designed for students with disabilities [27]. Barriers related to disability appear in other forms as well: the most commonly studied programming language is Scratch (19 papers), and four of the most cited papers concern block-based programming, but visually-based languages are not easily accessible for users with cognitive impairments [28] or, especially, limited vision [29]. (Text-based languages, such as Python – the second most commonly used in the data set – can also suffer from accessibility issues due to the fact that screen readers are generally not designed to read code, an issue especially relevant to the syntactical significance of white space in Python.) There has always been a moral case for ensuring that students with disabilities could access computing instruction, but that case is augmented by several factors including computer science graduation requirements in some locations and the increasing popularity of the computer science major.

4.5 Socioeconomic Status

Similarly, socioeconomic status is specified in only 14% of studies and prior computing experience in 33%; these factors have significant equity implications given that students attending under-resourced schools are less likely to have access to computer science [30] and Black and Hispanic students are less likely to have computers at home [31], with prior computing experience (i.e., preparatory privilege [32, 33]) shaping perceptions of who can succeed in computer science.

4.6 Race and Ethnicity

More research on the experiences of students from diverse racial and ethnic backgrounds is needed: only one of the most-cited articles is focused on students' racial and ethnic identity, and few papers specify the race (36%) or ethnicity (25%) of student participants. The proportion of papers that specify student race has decreased over the study period. Papers rarely mention the instructor race (7%) or ethnicity (3%), which makes it difficult to explore interaction effects between student and instructor identities.

4.7 Other Equity Issues

There are substantial gaps in the research related to equity concerns. For example, virtually no research (only 2 out of 231 studies) is focused on parents or the community. This may represent a lost opportunity for equity-enabling research to the extent that it suggests room for growth in culturally relevant and/or sustaining research studies, such as recent work on culturally responsive debugging that leverages community expertise [34].

Other potential gaps in equity-enabling research are less obvious: for example, interventions based on elective activities predominate (74%), perhaps due to the ease of studying student behavior in enrichment programs (e.g., summer camps and after-school programs) as opposed to in the formal classroom. But girls are less aware than boys are of these opportunities [31], which may lead to disparate participation rates by gender and, in turn, an evidence base that does not adequately reflect the experiences of all students.

Choices in research design may also impinge on equity issues. The most commonly used measurement tool, surveys, have differences in responses based on language and culture [35, 36]. For example, Asian students will, on average, be less likely to provide responses on the extremes to survey questions [37]. Similarly, interviews – the second most commonly used measurement tool – can be skewed by the racial biases of the interviewer [38]. Observation (the third most common measurement tool) has been shown to be impacted by the race or gender of the observer [39, 40].

Further, there is a distinction between *specifying* a factor and *analyzing* that factor: an article might specify how many girls, boys, and non-binary students participated in the intervention without analyzing the results based on gender (e.g., "there was no significant difference in test scores based on participant gender"). Many papers that specify an attribute do not analyze that attribute. Thus, while the percentages of studies specifying demographic factors is an important first step toward understanding whose computing experiences are being studied and to what extent research findings may be applicable in other contexts, analysis of the factor provides additional insight into whether the intervention being studied has a differential impact on various groups of students. While it is neither possible nor appropriate for *every* research study to analyze its findings based on every demographic factor, the overall lack of specified and analyzed factors results in a significant gap in the knowledge base regarding effective computing instruction.

Interestingly, the keyword *equity* does not appear in Figure 4 because it does not occur in more than 4 years, but it does appear among the most common keywords, pointing to a recent emphasis on the topic. In fact, *equity* is not used as a keyword until 2019, but it occurs each year thereafter. This finding is a positive indication of the increasing concern with equity in the computing education community.

4.8 Limitations

We acknowledge several limitations to this study. First, citation practices have been shown to be influenced by a variety of biases [41], making any analysis reliant on citation counts susceptible to reflecting underlying inequities in academic research. Second, the categorization of papers upon which this study is based has some subjective elements, which may impinge on the final data. Third, some of the factors assessed in this paper (e.g., student participant location) are not included in every study, which may skew some of the analysis, such as which geographic locations are more or less likely to be represented in the research data.

4.9 Recommendations

As the discussion above suggested, there is room for improvement in addressing equity issues in computing education research. We present the following suggestions for best practices for equity-enabling research:

Consider the equity implications of research methods. Choices in research design may have consequential but not obvious equity repercussions. As mentioned above, the three most common measurement tools – surveys, interviews, and observations – can have biases; researchers need to work toward mitigation of those biases. (In addition to equity concerns, previous research has found that most surveys designed for computing education research do not follow best practices for survey design [42]).

Appropriately specify and analyze demographic information. An intervention that shows promise in the aggregate may or may not be equally effective for all student groups. Thus, where possible, specify and then analyze demographic information. Several guides have been developed to help researchers appropriately gather demographic information [43–45]. It is important that survey questions present students with choices that reflect their identities, such as questions about gender that present it as more than a binary choice [46], because requiring a student to select a category that does not match their identity can in itself be oppressive [47].

Use accessible tools. Where possible, research studies should choose to use tools such as programming languages designed for accessibility [48], add-ons that make block-based programming accessible to blind and visually impaired students [49], and tools designed for students with hearing impairments [50]. This also includes carefully choosing tools for data collection that are also accessible.

Include details about interventions. Many studies do not indicate, for example, the grade level of students, their geographic location, or what programming language was used in the study. When this information is absent, it is difficult to draw conclusions about the landscape of extant research and what gaps might exist. It is also difficult for other researchers and for practitioners to determine how similar a study's context is to their own. While the vast majority of studies specified a research question, which concepts were taught, how data was measured, and the participant count, there is some room for improvement in each of these variables.

5 Conclusion

In sum, the result of our analysis of computing education research focused on high school students is that this expanding field is categorized by both much work on equity-related issues as well as by some significant gaps. In particular, studies tend not to focus enough attention on the needs of students with disabilities, and the use of common research methods (e.g., surveys) may enable various forms of bias. At the same time, it is heartening that almost half of the most-cited articles focus in some way on equity issues.

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