An Examination of Empirical Evidence Produced by a Decade of K-12 Computer Science Education Research

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***Abstract*—Problem. This full research paper describes the results of a literature review of data collected about K-12 computer science education research and initiatives. Over the last ten years, K-12 computer science (CS) education research has evolved to meet the needs and progress of the computer science education community. As a field, however, we have no empirical evidence of what this evolution is and how it has managed to produce the empirical evidence needed to support the long-term goals of computing education research as computing education grows into every primary and secondary classroom.**

Research Question. Our question for this study was *How has K-12 CS education research evolved over the last decade, including when examining the research based on standards and inclusion of student participants?*

Methodology. Using a publicly available database of curated articles documenting K-12 computing education research efforts, queries were run to extract pre-specified subsets of data. Descriptive statistics were calculated to identify trends to support answers to the research question.

Findings. We consider how this data reflects on changes in the last decade in light of the CS for All initiatives, including the fact that less than 5% of studies include students with disabilities and less than 20% of studies report participants' socioeconomic status. With the growth of computing in schools in the last decade, it is important to consider previous computing experience of students when analyzing results, but our data shows that only 40% of studies do.

Implications. The good news is that this increase means that more topics, contexts, and student subgroups can be explored each year, and new insights on best practices are likely to arise from these findings. The bad news is that the attention to the needs of historically marginalized groups is not increasing at the same pace. While our data shows modest to gradual increases in the percent of research articles that report on factors such as the student race and instructor gender, these factors are still rarely reported, which may make it more difficult to ensure that CS education research involves a wide diversity of participants.

***Index Terms*—Primary education, secondary education, K-12, research, disabilities, gender, race, locations, concepts, camps, schools, curriculum, activities, socio-economic status**

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I. Introduction and Background

It is well-established that computer science (CS) education has been increasing over the last decade, with growth most visible in primary and secondary schools. This comes as countries, regions/states and municipalities have adopted standards for offering CS to K-12 students and moved to implement curriculum to meet those standards [1].

This trend lends itself to investigating the education research being conducted in this space. As new as the curriculum and pedagogy is that is being delivered to students [2, 3, 4], the research into how impactful these practices and resources are is even fresher and remains of interest to researchers who want to understand where the greatest needs are. This especially true as K-12 computing reaches into the early elementary classrooms, where so many questions about what and how to teach computing remain unanswered. This type of research can provide insight into what may or may not be working for various populations of students [5].

Although still nascent compared to other education fields, K-12 computing education research is carefully being tracked longitudinally in limited studies [6, 7]. For example, one longitudinal study was conducted to predict women's persistence in CS and technology related majors from high school into college [8]. Warner et al. conducted a study on extant data to determine barriers to access and participation for high school students taking CS courses [9]. Another study by Proctor and Blikstein included students over three years (sixth through eighth grades) and examined student produced artifacts from their computing courses [10]. Their results indicated that student engagement had a larger impact on performance on tasks when compared to performance on previous projects.

Given this, we wanted to consider who and who is not included in research studies focused on K-12 CS education. The overarching research question for this study was: *How has K-12 CS education research evolved over the last decade, including when examining the research based on standards and inclusion of student participants?* For the purposes of this study, we define major trends to include:

- Locations of students/interventions studied

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- Program data (e.g., concepts taught, when activity was offered, type of activity, teaching methods),
- Student data (e.g., disabilities, gender, race/ethnicity, SES)
- Instructor data (e.g., race/ethnicity, gender)

Given the exponential growth of computing in formal K-12 education settings over the last decade, understanding research trends is critical to identifying emergent promising practices. In this paper, we discuss our secondary data longitudinal study methodology, results of analyzing major trends, and discuss these implications for CS education research.

This paper adopts the theoretical framing advanced by Strunk and Hoover, which grounds equity considerations in the gathering, analysis, and use of quantitative research data [11]. Specifically, they note that – despite common sentiment – quantitative research methods are not neutral nor are they objective, either in their history or in their current application. The assumption of neutrality and objectivity, especially in educational research, has led to concrete harms such as tracking minoritized children into paths that fit stereotypes of what is considered an appropriate education for people of their race, gender, and socioeconomic class. Secondly, Strunk and Hoover note that quantitative research is often grounded in an unquestioned culture of positivism, a view that implicitly disregards the potential contributions of any way of knowing that is not based in empirical research. Third, quantitative research often assumes a deficit framing: the assumption is that in cases where the performance of a minoritized group differs from other students, it is because the minoritized group is deficient in some way. On the other hand – but equally problematically – quantitative research can focus on traits such as resiliency or 'grit' in minoritized students without interrogating which students are required to develop these characteristics in the face of systemic injustice and which are not. The authors note that a new approach to quantitative research methods that does not fall prey to the problems outlined here is needed in order to promote equitable research practices.

II. Methodology

To answer our research question *How has K-12 CS education research evolved over the last decade, including when examining the research based on standards and inclusion of student participants?*, we used data from the K-12 CS Education Research Resource Center, a site that houses summaries of articles focused on K-12 computing education [12]. The manually curated data is derived from twelve publication venues (2012-2021) consisting of journals and conference proceedings related to computing education, including IEEE ASEE FIE[1]. Data curated from each paper includes those shown in Table I.

TABLE I
DATA MANUALLY CURATED FROM ARTICLES.

Data Type	
Title	Student Gender
Authors	Student Race
Keywords	Student Ethnicity
Page Numbers	Student Disability
Abstract	Student Disability Instruction Setting
Abstract Page Numbers	Student Disability Services
DOI	Student Socio-Economic Status
Venue	Student Prior Experience
Year Published	Student Location
Report Type	Course Curriculum Content
Focus Area	Number of Instructors
Basic Study Design	Instructor Prior Experience
Research Approach	Instructor Race
Research Questions	Instructor Ethnicity
Study Duration	Instructor Gender
Experience Report Description	Instructor Type
Gender Analyzed	Activity Goals
Race/Ethnicity Analyzed	Activity Learning Objectives
Socio-Economic Status Analyzed	Activity Curriculum
Concepts Taught	Activity Average Number of Students
Evaluation Measures	Activity Tools/Language
Measurement Frequency	Activity Type
Measurement Type	Activity Type (Elective/Required)
Type of Effect Size Reported	Activity Time
Statistics Reported	Activity Assignment Type
Number of Students	Activity Teaching Method
Student Age	Activity Duration
Student Grades	

Each article in each publication venue was examined to determine if it focused on K-12 computing education, and if so, the data from the article was manually curated and added to the dataset. The data curation process is explained in greater detail in prior studies and at the Center's site [6, 13, 14, 12].

To identify the major trends across a decade, one of the researchers conducted queries over the entire dataset, extracting pre-specified subsets of data (further discussed in the next section). Only research articles (n=642) were included (not, for example, experiences reports, position papers, and posters) and descriptive statistics (count and percentage) were calculated for the predetermined trends being examined for this study. For each paper, the citation count (as of May 2023) was taken from CrossRef [15]; for the approximately one dozen papers in the dataset that did not have CrossRef entries, the citation count was taken from Google Scholar. Data on country and US state student populations from the UNESCO via the World Bank [16] and from the National Center for Education Statistics [17]. Where possible, 2019 student population data was used

[1]The publication venues include: 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), and Workshop in Primary and Secondary Computing Education (WIPSCE).

to avoid pandemic-related disruptions.

Overall, the data set includes 1,484 authors, affiliated with 508 different institutions. Figure 1 shows the number of organizations in the data set each year; there is some volatility from year to year, but an overall trend of an increasing number of different organizations per year on average.

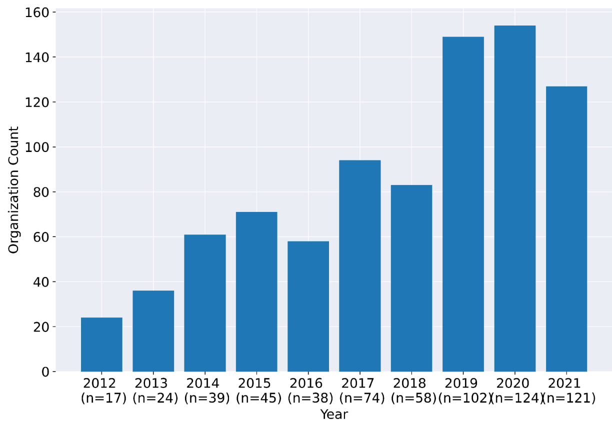

Fig. 1. Count of organizations by year.

Table II shows the institutions most often represented in the data set.

Organization	Count
North Carolina State University	29
University of Chicago	27
University of Florida	22
Georgia Institute of Technology	19
Michigan State University	16
SRI International	13
University of Pennsylvania	12
The University of Adelaide	12
The Findings Group	11
University of Colorado Boulder	11

TABLE II
RESEARCH ARTICLE COUNT FOR THE TEN MOST COMMON INSTITUTIONS IN THE DATA SET.

The average paper count per author is 1.6. Table III shows the authors with the most papers in the data set; Diana Franklin is listed as an author on nearly twice as many papers as the next most prolific author. Nine of the ten most prolific authors are based in the United States (US); one, Sue Sentance, is based in the United Kingdom.

Name	Count
Diana Franklin	28
Tiffany Barnes	17
David Weintrop	13
Monica M. McGill	12
Aman Yadav	12
Sue Sentance	12
Kristy Elizabeth Boyer	11
Jean Salac	11
Tom McKlin	10
Shuchi Grover	10

TABLE III
RESEARCH ARTICLE COUNT FOR THE TEN MOST PROLIFIC AUTHORS IN THE DATA SET.

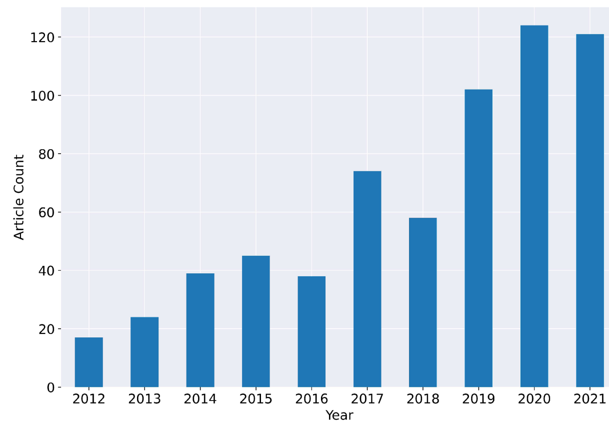

Fig. 2. Count of research papers by year.

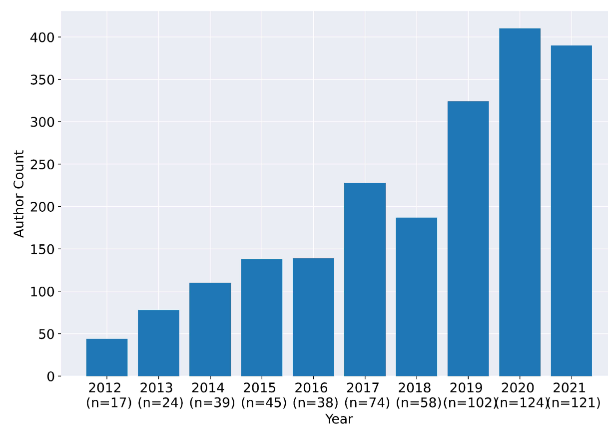

Fig. 3. Count of authors by year.

III. RESULTS

This section presents findings related to the research itself, to student participants, and to instructor participants.

A. The Research

The dataset indicates a rapidly increasing number of published research articles about K12 CS: the average yearly growth rate for research articles was 30% (see Figure 2) and for number of unique authors was 32% (see Figure 3).

For each paper, the average number of citations per year was calculated by dividing the total number of citations by the number of years since the article was published. Table IV lists the papers with the highest average number of citations per year. Two of the most-cited articles focus on the experiences of girls, and one additional article includes *equity* as a keyword; no title or keyword refers to the experiences of other historically marginalized groups.

B. The Students

Figure 4 shows the number of students in each study (with outliers omitted). The most common number of participants was between 101 and 500. For the subset of articles which

Title	Count
TechCheck: Development and validation of an unplugged assessment of computational thinking in early childhood education	45
Computing whether she belongs: Stereotypes undermine girls' interest and sense of belonging in computer science	43
Computational thinking, mathematics, and science: Elementary teachers' perspectives on integration	38
Programming experience promotes higher STEM motivation among first-grade girls	38
Computational thinking in elementary and secondary teacher education	34
A critical review of literature on "unplugged" pedagogies in K-12 computer science and computational thinking education	32
Designing for deeper learning in a blended computer science course for middle school students	31
Measuring student learning in introductory block-based programming	30
Expanding computer science education in schools: Understanding teacher experiences and challenges	27

TABLE IV
PAPERS WITH THE HIGHEST RATES OF CITATIONS PER YEAR.

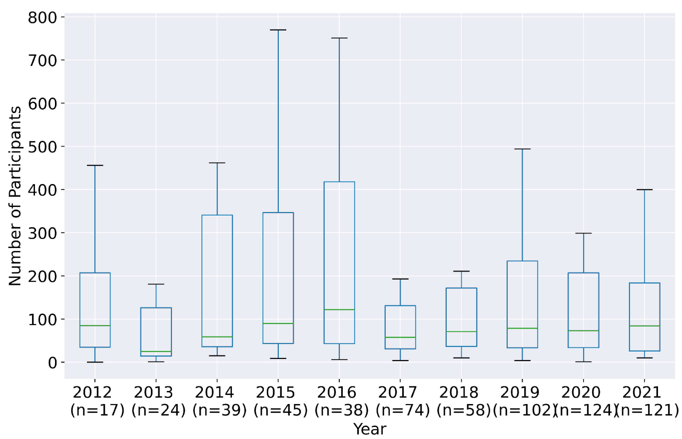

Fig. 4. Count of participants per study (outliers omitted).

specified whether participation in the activity was required or was elective for students (n=165), 78% of studies involved elective experiences.

For those articles where it was applicable, 72% specified the location of the research study. Of those, 46% were in the US, 51% were outside of the US, and the remainder were co-located, although these percentages have some volatility over time, as Figure 5 shows. Given that the US accounts for less than 5% of the world's K-12 students, American students are substantially over-represented in research studies.

Table V shows the paper count by country for the ten most prolific countries. Paper counts were then scaled to the country's student population by dividing the number of papers per country by the number of students per country (and then multiplying by one million for readability). Table VI shows that data scaled to the country's K-12 population for countries with at least four research papers, for the countries with the highest ratio of publications to students.

While more papers feature students from the US than from any other country by a factor of more than five, the US has only the ninth highest number of papers once the count is scaled according to its K-12 population. Similarly, Germany drops from second in raw paper count to tenth in scaled paper count. When a country's student population is taken into account, Finland is at the top of the list, with New Zealand, Greece, Ireland, and Austria composing the remainder of the top five countries.

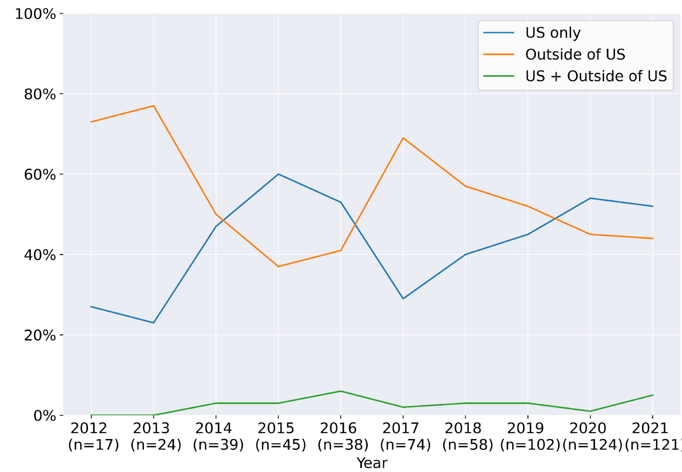

Fig. 5. Percent of studies located in or out of the US.

Country	Count
United States	188
Germany	36
United Kingdom	34
Australia	13
Finland	12
Brazil	11
Israel	9
Netherlands	9
Greece	9
Sweden	8
total papers worldwide	642

TABLE V
RAW PAPER COUNT BY COUNTRY.

Country	Count
Finland	13
New Zealand	8
Greece	6
Ireland	5
Austria	5
Switzerland	5
Israel	4
Sweden	4
United States	3
Germany	3

TABLE VI
PAPER COUNT SCALED TO STUDENT POPULATION.

Tables VII and VIII show raw and scaled counts (for states with at least three papers) for papers by US state. No studies were conducted in 22 US states: Alaska, Alabama, Arkansas, Hawaii, Kansas, Kentucky, Louisiana, Minnesota, Mississippi, Montana, North Dakota, Nebraska, New Hampshire, Nevada, Ohio, Oklahoma, Rhode Island, South Dakota, Tennessee, Vermont, West Virginia, Wyoming. The most prolific states by raw paper count are California and New York, although they drop (to seventh and second place respectively) when paper counts are scaled according to states' K-12 population.

Figure 6 shows the raw counts of papers per US state over the study.

Figure 7 shows the raw counts of papers per country over the study for each country that had at least two papers in one or more years.

The student participants' socio-economic status was specified in some way in 16% of research articles, and 7% of

State	Count
California	23
New York	13
Illinois	9
Georgia	8
Texas	8
North Carolina	6
Virginia	4
Massachusetts	4
Iowa	3
Florida	3
total papers US	176

TABLE VII
RAW PAPER COUNT BY US STATE.

State	Count
Iowa	6
New York	5
Illinois	5
Georgia	5
Massachusetts	4
North Carolina	4
California	4
Maryland	3
Virginia	3
Texas	1

TABLE VIII
PAPER COUNT SCALED TO STUDENT POPULATION.

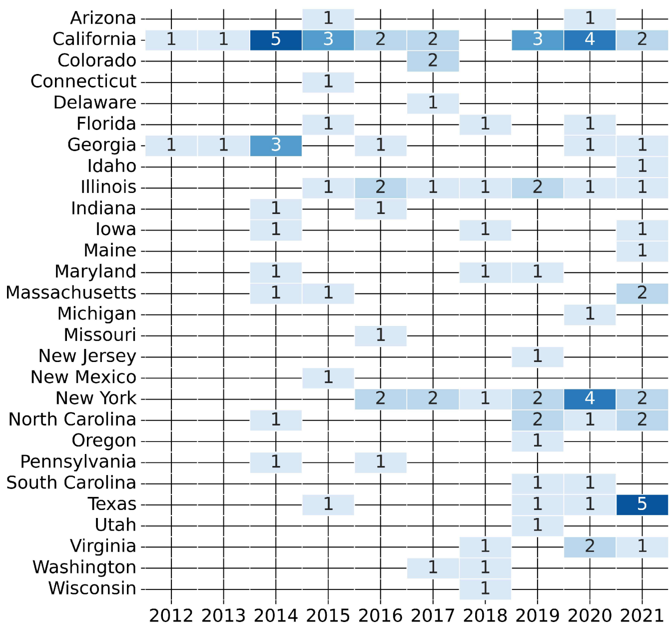

Fig. 6. Counts of papers by location for US states.

studies analyzed socio-economic status. As Figure 8 shows, these rates are roughly stable over time.

Only 2% of papers included student disability status. Until 2017, no articles specified student disabilities where it would have been applicable. Since 2017, between 2% and 5% of papers have specified student disabilities.

About two-thirds (64%) of papers specified student gender. Interestingly, the percentage of papers reporting gender is decreasing slightly (see the trend line in Figure 9). Overall, 35% of papers analyzed gender, and this rate is quite stable over time.

Data on student race was reported in 30% of papers and data about ethnicity in 20% of papers. Race and/or ethnicity was analyzed in 19% of papers.

Figure 10 shows that race is reported more often than ethnicity, and neither has been reported in more than 40% of studies. Both show a trend line for increased reporting over the decade represented in the dataset.

Where applicable (n = 196), 22% papers specified whether students were English language learners.

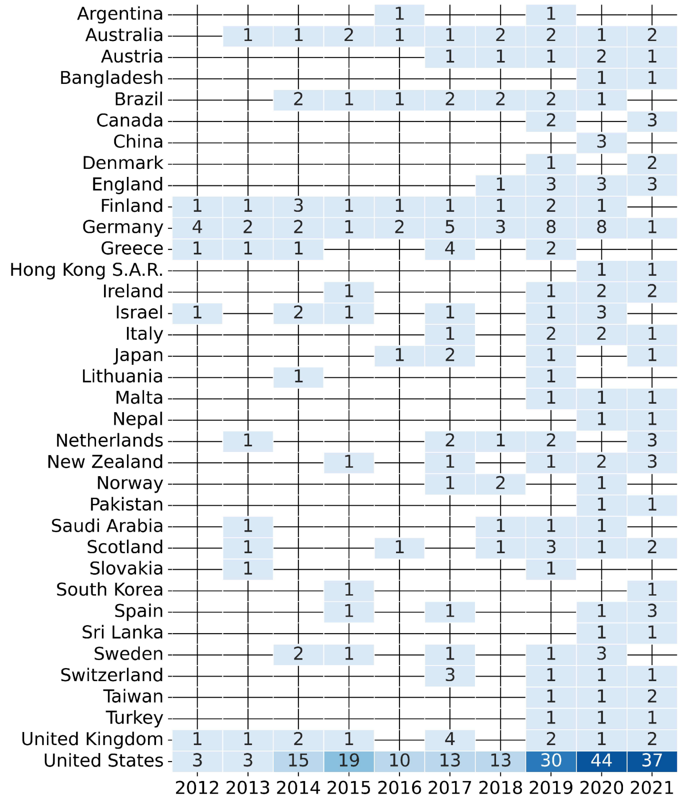

Fig. 7. Counts of papers by location for countries with at least two papers.

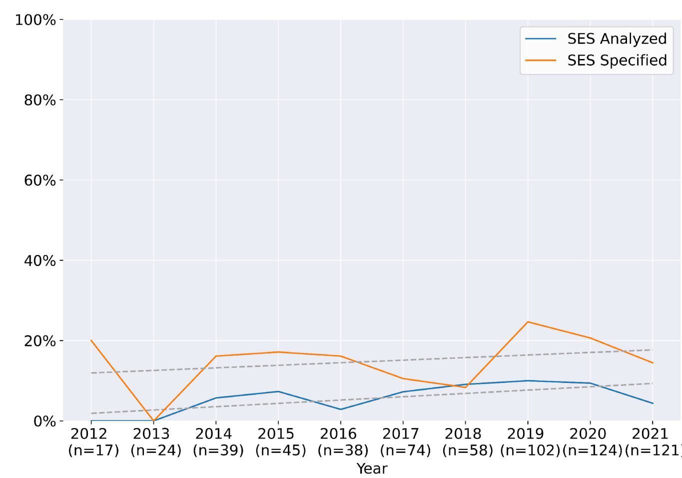

Fig. 8. Percent of papers specifying and analyzing data about participant socio-economic status (SES). Articles where SES data is analyzed are a subset of the count of articles where SES is specified.

About one-third of papers (32%) specify students' prior CS experience, a percentage that is quite stable over time despite year-to-year volatility, as Figure 11 shows.

Table IX shows the count of papers that included some form of intersectional analysis.

Figure 12 shows the relative frequencies of the keywords for articles that provide intersectional analysis by analyzing participant data by socio-economic status, gender, and race/ethnicity,

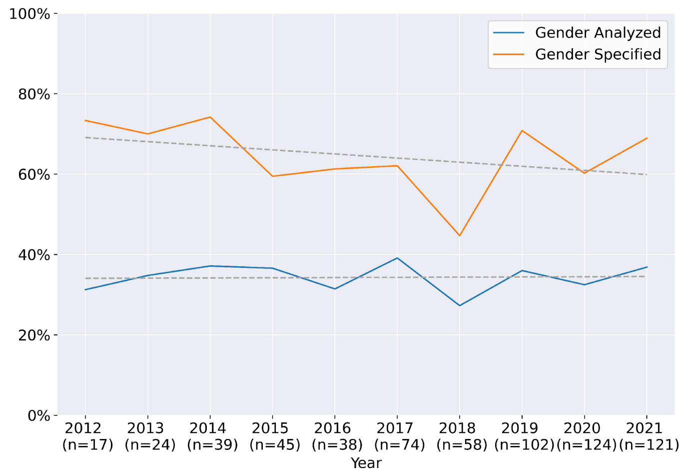

Fig. 9. Percent of papers specifying and analyzing data about participant gender.

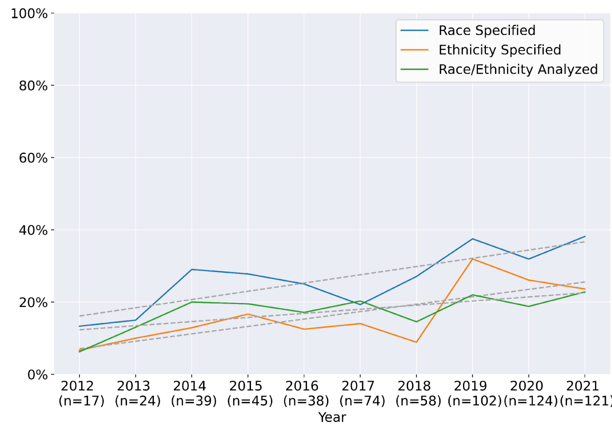

Fig. 10. Percent of papers specifying and analyzing data about participant race and/or ethnicity.

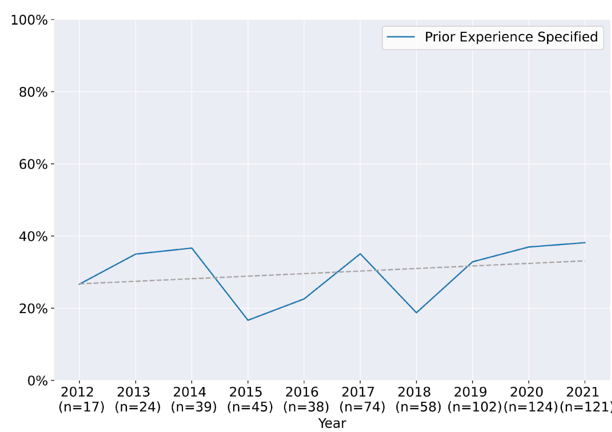

Fig. 11. Percent of papers specifying data about participant prior experience.

the last row of Table IX. Note the prominence of the keyword 'case studies'. It appears that many articles with intersectional analysis of this type are case studies.

Intersections	Count	Percent
Socio-economic status and gender	25	4%
Socio-economic status and race/ethnicity	33	5%
Gender and race/ethnicity	97	15%
Socio-economic status and gender and race/ethnicity	23	4%

TABLE IX
RESEARCH ARTICLES INCLUDING INTERSECTIONAL ANALYSIS.

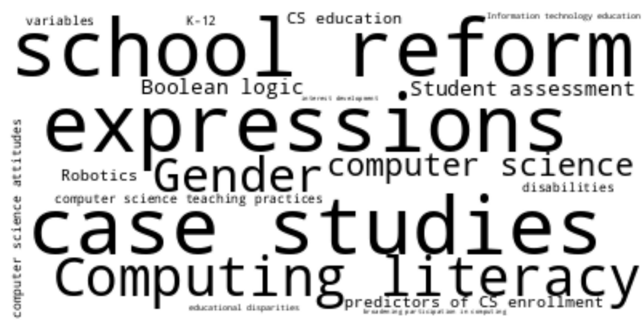

Fig. 12. Word cloud of keywords in articles that analyzed participant data by socio-economic status, gender, and race/ethnicity.

C. The Instructors

Figure 13 shows modest growth over time for the percent of papers reporting various instructor characteristics and attributes.

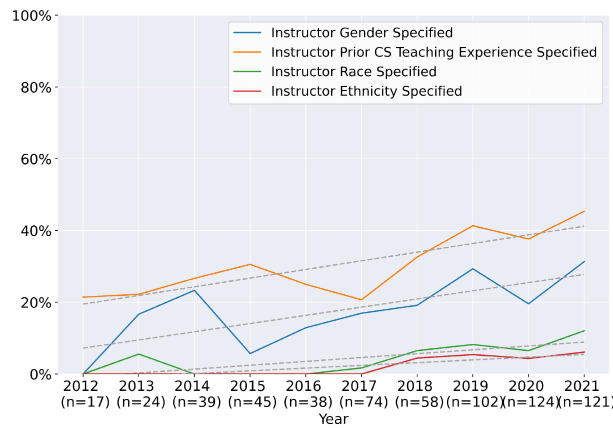

Fig. 13. Percent of studies specifying instructor characteristics and attributes.

Table X shows the percent of articles which specify various instructor characteristics.

Characteristic	Percent
Prior CS teaching experience	34%
Gender	21%
Race	6%
Ethnicity	3%

TABLE X
PERCENT OF ARTICLES SPECIFYING INSTRUCTOR CHARACTERISTICS.

Table XI shows the count of papers specifying instructor race.

Out of the 101 papers which specified instructor gender, 91 specified women and 83 specified men.

Race	Count
Latino	17
Asian/Pacific Islander	15
Black or African American	13
White	11
Caucasian	8
American Indian or Alaska Native	8
Other	5
Multiracial	4

TABLE XI
INSTRUCTOR RACE WHERE SPECIFIED.

IV. DISCUSSION

Based on the data, there is clearly an increase in the rate of publication focused on K-12 CS education over the past decade. However, it is also the case that a majority of the work being published in the venues represented by the dataset is from the US. When looking at that data scaled by student population, however, the US does not remain as the most prolific producer despite it being oversampled in this dataset.

Education is controlled at the state level in the US, not at a centralized national level. Standards, accreditation, and other educational decisions are largely left to each state and the education systems vary widely from state to state. It is clear from looking at the data that certain states are far more represented than other states in the dataset. Almost half (22) of the 50 states are not represented at all with papers about K-12 CS education. This limits our understanding of K-12 CS education across most of the country. Even within the most populous states (California, Texas, Florida, New York), we don't see a proliferation of articles about efforts in those states. In fact, they are not even the top four states where interventions are held.

It is interesting to note within the articles just how often certain demographics of student participants in studies are reported upon. In the case of most of the demographics in Figures 9, 10, 11, and 13, we see what appears to be a slight increase in reporting when compared to Decker and McGill's previous work. The earlier research points out gaps in reporting in K-12 CS education studies and includes recommendations for better reporting of many aspects of these research studies, including student demographics [7].

When considering the reporting of race/ethnicity, we risk the "securing Whiteness" by not making visible all participants' races/ethnicities [18]. It may be the case that studies should move towards not just reporting race/ethnicity of participants, but also noting when participants from those groups are part of marginalized groups within the context of the location of the study. Given the global nature of publication and ease of access to electronically published articles, it is not always the case that readers will be familiar with the local context of any aspect of the work. Explicitly collecting and reporting of this data, as appropriate and ethical, can provide deeper insight into these contexts.

Given the increased interest in K-12 CS education research and the expansion of K-12 CS education standards in many states within the US, the growth of articles and studies is not surprising. However, one demographic characteristic that is definitely under-reported is percentage of students with disabilities in the population studied/classroom. In the US, 15% of school aged children receive services for special education needs [19]. In addition, students who are English Language Learners are a group whose learning may need to be assisted differently than students where English is their first or fluent language. A definite area for growth in research is with these two groups of students to study how the impact of CS education initiatives impact non-typical learners both in the US and elsewhere. Further, of the studies that included the type of experience, 78% involved elective experiences. However, girls are less likely than boys to be aware of or to choose to participate in CS elective studies [20]. This indicates yet another opportunity to grow the research on the ever-expanding formal CS education.

In addition to atypical learners, the increase of availability of CS education at the K-12 level has caused there to be differences in prior preparation of students. Based on our analysis, only about one-third of the papers provide data on prior experiences. As initiatives continue to grow and mature, researchers need to be aware of what prior knowledge and CS exposure students bring to the intervention/classroom. This information can impact results and should be taken into consideration during study design.

The impact of intersectional identity on human experiences is understudied in this corpus of literature over the past ten years. When it has been studied, there seems to be a prevalence to case studies as the primary vehicle to study intersectional populations. This is likely due to the small numbers of participants that would fall into each intersectional identity. As we continue to expand CS education into more educational settings, participants with certain intersectional identities will grow and larger number of participants in studies will be possible. It is critically important that as a field we embrace qualitative methods and their findings to help better understand unique participant identities and their experiences learning CS.

Lastly, we note that many articles miss the opportunity to report on the demographic characteristics of instructors/leaders of the classrooms/interventions, except in the case when the instructor/lead is from a traditionally marginalized group. Research shows that instructors influence the classroom and the influence of who is presenting the material matters [21, 22]. As noted by a study by Heckman et al. with which our findings support, collecting and reporting on this information is essential in helping others to understand the impacts of an intervention [23].

A. Limitations

A major limitation of this work is that the data is derived strictly from the dataset housed in the CS Education Research Resource Center [12]. However, at present, the resource center curates from twelve publication venues, including top conferences and journals in the area of CS education research and has a robust process for curating data.

Another important limitations to address is what role human error could have both in the creation of the data set and in the querying, cataloging, correlating, and analysis of data by the researchers. In addition, we can only aggregate and measure what is reported upon in the articles. If information is gathered during the research process from the participants, but never published, it cannot be considered nor included in this analysis.

Finally, the nature of the underlying data circumscribed the kinds of analysis that were possible to perform. For example, Strunk and Hoover note that the categories for race and ethnicity used in most surveys may not reflect the lived experience of all respondents, especially in situations where their distinct racial identity is collapsed into "multiracial" or "other." Similar issues arise with respect to gender. They recommend collecting these types of demographic data through free response questions that permit respondents to choose the terminology which they believe best describes themselves or, when the scale and/or coding of data make free response impractical, to carefully phrase questions to acknowledge their limitations (e.g.,"choose which category best describes you, even if none is an exact match to your identity"). We also acknowledge that no data analysis is strictly objective or neutral. For example, other researchers may have chosen different variables, combinations of variables, or data visualizations – each of which would have suggested a different interpretation of the underlying data.

V. Conclusion

The high yearly growth rate of research articles in the dataset – nearly one-third on average – speaks to the rapidly increased activity in the field of K12 CS education. The good news is that this increase means that more topics, contexts, and student subgroups can be explored each year, and new insights on best practices are likely to arise from these findings. The bad news is that the attention to the needs of historically marginalized groups is not increasing at the same pace. While our data shows modest to gradual increases in the percent of research articles that report on factors such as the student race and instructor gender, these factors are still rarely reported, which may make it more difficult to ensure that CS education research involves a wide diversity of participants. CS education research is conducted disproportionately by researchers in and involving students in the US, which may mask the different contexts and experiences of researchers and students in other nations. Similarly, very little research reports about student disabilities. Advancing equitable CS instruction will require rectifying these disparities.

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