Intersectional Factors that Influence K-2 Students' Computer Science Learning

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ABSTRACT

Understanding issues of intersectionality in education is vital for creating equitable learning environments. Intersectionality emphasizes the complexity of students' identities, including race, gender, and socioeconomic status, and how they interact to characterize their diverse group membership. Examining data intersectionality underscores students' heterogeneous needs, circumstances, and outcomes, advancing researchers' and policymakers' understanding of the types of interventions that ameliorate disparities for marginalized students. This study examines the intersectional factors influencing K-2 students' coding skills. We employ a hierarchical linear model on a validated pre-and-post coding assessment to examine a year-long Coding as Another Language curriculum for Latine, multilingual, and low-socioeconomic students. Findings indicated initial performance gaps for students with historically marginalized and intersecting backgrounds. After receiving the curriculum, these students demonstrated significant improvement, closing the coding skills gap with their more privileged peers. These findings underscore the importance of investigating and mitigating disparities in coding education for students with intersecting identities.

CCS CONCEPTS

• **Social and professional topics** → **Computing education**; **Computational thinking**; **K-12 education**;

KEYWORDS

computer science education, intersectionality, coding, multilingual, English learner, Latine, early childhood education, K-2

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There is a trend in computer science (CS) education to tailor curricula to specific demographic groups, but this is complicated by students with intersecting backgrounds. Intersectionality encompasses multifaceted identities, including Latine students designated as English learners, which unveil systemic factors that contribute to compounded marginalization [12, 39]. Incorporating intersectionality into discussions about computer science education highlights how the experiences of marginalized students originate from complex interactions involving factors such as race, class, and gender [10, 12, 23, 36], and also has significant policy implications. It underscores the need for educational policies to recognize and address these complexities, ensuring that interventions in computing education are inclusive for students from historically marginalized and intersecting identity groups.

In a recent paper on diverity in CS, Salac et al. [41] undertake a comprehensive examination of computer science learning, exploring the effectiveness of the TIPP&SEE scaffolding strategy [42] in supporting a diverse group of fourth graders. The inclusive study encompassed students with low socioeconomic status, multilingual backgrounds, and emerging reading and math scores. Analytically, this paper builds off of Salac et al.'s [41] examination of diverse student group performance by specifically investigating how demographic factors—such as race, language, and class—intersect to shape the learning experiences of students engaging with computer science. In doing so, we seek to advance our understanding of the nuanced interplay of these intersecting characteristics in the context of learning to code.

To exemplify intersectionality's role in exacerbating marginalization, we investigate CS education for predominantly Latine and multilingual students from low-socioeconomic backgrounds. Firstly, multilingual students, constituting over 25% of California's public school K-2 students with rising numbers [33], remain notably underrepresented in computer science education and achievement compared to other groups [29]. Secondly, the majority of US K-12 multilingual students are Latine [33], yet these intersecting identities see significant underrepresentation in computer science [28]. Thirdly, CS disparities are amplified in low-income neighborhoods, where fewer computer science courses are offered compared to affluent areas [9]. This constellation of factors demonstrates how intersectionality magnifies marginalization, revealing substantial disparities in computer science representation, access, and achievement among predominantly Latine and multilingual students from low-socioeconomic backgrounds.

While there are many programs to diversify the computer science pipeline in secondary and postsecondary school, there is an increasing recognition that efforts must begin earlier to achieve success [2, 4, 6, 9, 45]. Students' identities as scientists—and, for some, phobia of science—begin developing in early childhood [8, 21, 47]. The importance children give to a subject in elementary school can predict the number of classes in that subject they take in high school [20] and their early motivational beliefs can predict their achievement choices [18, 31, 50]. Programs targeting young learners are especially important in CS, a subject in which knowledge, skills, and attitudes are frequently tied to what students learn outside the classroom during elementary and middle school [6, 7, 19]. Allowing young children to learn about CS opportunities allows them to start developing positive attitudes and, ultimately, their identity and interest in the field and increases student motivation to pursue technology-rich education pathways [24, 26, 27, 49].

There is a growing body of research on providing computer science in early childhood education [5–7], yet few studies examine the ways in which intersectionality contributes to CS learning. This study explores the intersectional factors that influence the pre-existing knowledge and learning of coding for K-2 students through their participation in the Coding as another Language Curriculum [6]. The findings from this study will be used to highlight implications for policymakers on examining issues of intersectionality in CS education for predominantly Latine, low-income, and multilingual students.

0.1 Research Questions

- RQ1: What are the intersectional differences in K-2 students' pre-existing coding skills who have not received prior yearlong instruction in computer science?
- RQ2: To what extent do K-2 students' coding skills change after participating in the Coding as Another Language curriculum?
- RQ3: What are the intersectional differences in K-2 students' coding skills after participating in the Coding as Another Language curriculum?

1 POSITIONALITY

The research team, composed of educational researchers united by their focus on equity in education, brings a diverse array of perspectives and experiences to their work. Among the team members, two identify as Latine, and the majority are bilingual or grew up speaking a language other than English, highlighting their comprehensive understanding of multilingual and multicultural contexts. The first author's background as an Egyptian American raised in a high-poverty household with disabled parents has fueled her commitment to embracing and celebrating diversity in language, ethnicity, ability, and income in both her teaching and research endeavors. Other collaborating authors, with their varied experiences as immigrants, bilingual individuals, and members of culturally diverse communities, contribute knowledge gained from their lived experiences to highlighting the assets of culturally and linguistically diverse students. All authors, as educators deeply committed to researching educational equity, aim to increase participation for diverse learners and enrich the research process. The team collectively strives to remain open to a wide range of interpretations and perspectives, extending beyond their individual experiences.

2 BACKGROUND

Extensive research addresses barriers to STEM achievement, see [32] and computing performance [15, 42], yet limited investigation focuses on the impact of intersectionality on achievement for marginalized students in computing with intersecting backgrounds [39]. Scott et al. [43] identified a noteworthy gap in CS engagement between genders. Their study revealed disparities that existed between elementary girls and boys in terms of their attitudes toward computer science. Building on this, Rodriguez et al. [38] extended the investigation to cultural gaps. Their research specifically illuminated challenges faced by Latina students who grapple with envisioning themselves as potential scientists or mathematicians within the CS field. Echoing this intersectional perspective, Rodriguez and Lehman [39] emphasized the complex interplay of CS identities, highlighting how they intersect to create distinct challenges for marginalized groups.

This alignment between research studies points to the intricate nature of the relation between CS learning and issues of intersectionality. As students engage in CS learning, their various group memberships, including gender, language, socioeconomic status, and race interact and often compound the experience of marginalization [44]. Therefore, understanding CS learning within these intersections becomes crucial for addressing the needs of diverse student populations, especially in early elementary grades.

3 THEORETICAL FRAMEWORK

We ground our study within frameworks of intersectionality, drawing upon influential works in the field [1, 17, 44]. In the context of computing education, intersectionality serves to explore how particular instances of oppression influence the experiences of students from marginalized backgrounds [10, 12]. Intersectionality situates oppression as a sociopolitical phenomenon, offering insights into how power systems govern relationships among individuals, groups, and social structures, contingent upon factors such as race, gender, language, and class [23].

By employing an intersectional lens, the study emphasizes the need to understand the power dynamics at play in educational settings [22]. This involves recognizing how institutional policies, societal norms, and historical legacies of discrimination and exclusion impact students' opportunities and experiences in learning computing. For instance, students from marginalized racial or ethnic backgrounds face stereotypes and biases that affect their identification with computing [48], a field traditionally dominated by privileged demographic groups.

A salient facet of intersectionality pertains to the contextual nature of power dynamics, wherein the experiences of individuals, such as Black or Latine women in STEM, can diverge from those of white women [40]. These nuanced experiences underscore the importance of grasping the historical and political forces that mold diverse group membership, a necessity that has been highlighted by recent scholarship [34, 35]. This multifaceted understanding enriches the study of intersectionality's implications within the realm of computing education.

4 OVERVIEW OF THE CURRICULUM

Coding as Another Language [6] is a set of curricular units for kindergarten, first, and second grade that embody the DevTech Research Group's guiding frameworks for teaching coding in early childhood with ScratchJr [14], a block-based visual programming language designed for coding in children ages 5-8. The Coding as Another Language curriculum emphasizes communication and self-expression, systematically drawing parallels between programming and natural languages in age-appropriate ways. In a randomized control trial examining the implementation of the CAL curriculum with 1057 students, findings indicated that the curriculum was effective in improving students programming skills [51].

The curriculum is freely accessible online. The technology-infused curriculum strengthens students' disciplinary understanding of and skills in CS as well as important affective outcomes. Additionally, basic concepts in literacy and math are aligned with CS in an integrated way.

Each grade-level curriculum consists of 24 lessons of 30-45 minutes that engage young children in developing computational thinking, problem-solving, and collaboration skills, while they learn to create their interactive projects with ScratchJr. Based on pilot studies conducted by [25], there are three elements of the curriculum that make it particularly suitable for Latine and multilingual students: coding and literacy integration, storytelling, and collaboration. Below is an elaboration of how the Coding as Another Language curriculum achieves these three goals.

4.1 Coding and Literacy Integration

The Coding as Another Language curriculum is specifically designed to align with students' developmental progression in an integrated learning environment that combines coding and literacy. Drawing inspiration from well-established research on literacy development, CAL identifies six progressive stages of coding development: emergent, coding and decoding, fluency, new knowledge, multiple perspectives, and purposefulness [6]. It also links powerful ideas in coding to those in literacy, such as sequencing [6]. An example activity might include cutting sentence strips into words and having students arrange the words in the correct sequence and order, discuss those concepts, and then proceduralize their knoweldge in ScratchJr.

The Coding as Another Language curriculum further takes an asset-based approach that values the use of multiple languages as all materials are translated into Spanish. While many educators believe that multilingual students must learn English before taking CS courses, research indicate that multilingualism enhances content learning [16, 46]. In fact, multilingual students increase language and content learning when compared to their monolingual, English Only counterparts [16].

4.2 Storytelling

Rooted in indigenous traditions, Latine communities possess a rich history of oral storytelling, a practice extensively utilized to convey cultural knowledge [30]. This form of storytelling serves multifaceted roles, encompassing the transmission of values, traditions, and cultural heritages [37]. The curriculum purposefully includes storybooks such as "Queen of Computer Code" to illustrate the contributions of pioneers in computer science. Moreover, children's stories such as "Stellaluna" are employed as instructional aids to clarify coding-related themes, such as persistence. Teachers are encouraged to substitute these designated storybooks with their own selections, as the designed activities are open-ended and intended to facilitate the teaching of coding concepts through literacy learning. The Coding as Another Language curricular approach also encourages students to share their imaginative narratives, embedding CS education within contexts that resonate with their own lives.

4.3 Collaboration

Studies indicate that Latine students tend to gravitate towards collaborative learning approaches, differing from individualistic methods [11]. When learners from historically marginalized backgrounds interpret their classroom interactions as emphasizing competition over collaboration, their engagement with science can wane, as they attribute this disengagement to a mismatch with their cultural values [3]. During the implementation of the Coding as Another Language curriculum, children are encouraged to share their programs with their peers. Jacob et al [25] found that Latine and multilingual children who participated in the Coding as Another Language curriculum received peer support and learned from peer feedback when developing coding projects in ScratchJr.

5 METHODS

5.1 Study Context

The current study examines the extent to which the Coding as Another Language curriculum, which was piloted "as is," supports students' coding skills. We worked in a large urban school district and a dual immersion school, both with among the largest percentages of Latine students (96%), students designated as English learners (40%), and students receiving free or reduced priced lunch (60%). A total of 17 teachers across 5 elementary schools participated in the study. For the purpose of this study, we look at two sources of data, a pre-and-post coding assessment and district demographic data to better understand the intersectional factors contribute to the development coding skills in culturally and linguistically diverse classrooms.

The teachers in the study participated in a two hour professional development to acquaint them with the CAL curriculum and ScratchJr and they met for monthly co-design meetings throughout the year to inform future potential refinement of the curriculum for the district and schools' diverse learners.

Teachers implemented the curriculum throughout the year once a week for 45 minute lessons. Teachers were encouraged to choose the time in which they would teach the CAL curriculum during the elementary school day. Because students could only be tested one at a time, and the test can take up to and over 45 minutes, testing all students was not possible. Based on a power analysis, the project team determined that at least 100 students be assessed to yield sufficient power. Students were tested on their coding skills both before and after the intervention, resulting in a final sample of 103.

5.2 Research Design

Results were analyzed using quantitative statistical methods. To measure student performance, a pre-and-post-test design was employed using a validated coding assessment, the Coding Stages Assessment [13]. To evaluate student performance, a hierarchical linear model was used to estimate differences in average scores across intersecting group characteristics and standard errors clustered at the classroom-level, with controls for teacher, grade-level, and parents' educational attainment. These estimated coefficients were then aggregated to present reference averages for each intersectional group identity and used to construct z statistics evaluating the significance of contrasts between and across the groups' pre-test and post-test scores.

6 DATA SOURCES

6.1 Coding Stages Assessment

Coding knowledge was assessed using a validated individual pre-post task-based assessment, the Coding Stages Assessment (CSA) [13] that takes under 45 minutes to complete. The CSA, available in Spanish and English, aims to identify which coding stage a child is at by asking them 6 questions from each stage. CSA's concurrent criterion validity was assessed by correlating scores with a K-2 computational thinking assessment, TechCheck, finding a moderate positive correlation (r = 0.55, $p < 0.01$). Mean inter-item correlation of the CSA was 0.24, sufficient for a unidimensional construct. Internal split-half reliability was excellent, with lambda = 0.94 (using Guttman's Lambda 6).

6.2 Secondary Data

The CSA data was merged with district-provided demographic data including students' grade, classroom assignment, language learning status, gender, free- or reduced- lunch program eligibility, and parental education achievement. Students' with complete pre- and post-test data were successfully matched to the demographic data, providing 103 observations.

6.3 Participants

This study's analysis sample included 103 students. See Table 1 for a breakdown of student demographic characteristics.

Table 1: Number of Students in Each Demographic Category

	English Learners		
	Full Pay Lunch	Free/Reduce Lunch	All Lunch
Male	6	20	26
Female	4	12	16
All Gender	10	32	42
	English Only		
	Full Pay Lunch	Free/Reduce Lunch	All Lunch
Male	17	18	35
Female	17	9	26
All Gender	34	27	61
	All Language Status		
	Full Pay Lunch	Free/Reduce Lunch	All Lunch
Male	23	38	61
Female	21	21	42
All Gender	44	59	103

7 DATA ANALYSIS

The data analysis focuses on characterizing the intersectional properties of CSA test scores in the pre-test, post-test, and the change in post- minus pre-test. The analysis identifies differences in CSA scores among intersecting language learning (English-Only / English Learner), socioeconomic (Free-and-Reduced Lunch / Full Pay Lunch), and gender (Male / Female) demographic characteristics. These characteristics result in a $2 \times 2 \times 2$ design to characterize differences in average CSA test scores within and across these groups after introducing categorical variables to control for grade, teacher, and parents' educational attainment.

To evaluate student pre-test performance, a hierarchical linear model was used to estimate differences in average scores across intersecting group characteristics and standard errors clustered at the classroom-level, with controls for teacher, grade-level, and parents' educational attainment. The estimated coefficients were aggregated to calculate reference average scores for a student in a first-grade classroom with the median-teacher whose parents are High School Graduates. Contrasts are drawn based on the difference in predicted reference scores for the different subgroups. Standard errors for these estimated coefficients and resulting aggregated differences are calculated from a Hierarchical Linear Model with controls for teacher, grade-level, and parents' educational attainment, clustered at the classroom level. The significance of any contrast was evaluated using z statistics. A similar analysis was applied to evaluate students' post-test performance.

To evaluate changes in student performance, a histogram was generated for the difference in students post-test scores and pre-test scores. These scores were initially compared without auxiliary controls using a paired t-Test. As with the pre-test and post-test score analysis, a hierarchical linear model was used to estimate differences in the changes in average scores across intersecting group characteristics with controls for teacher, grade-level, and parents' educational attainment. Reference average changes were then calculated for a student in a first-grade classroom with the median-teacher whose parents are High School Graduates. Standard errors are calculated with clusters at the classroom level and z statistics evaluate the significance of any difference.

Table 2: Reference Pre-Test CSA Average Scores

	Full Pay Lunch	Free/Reduce Lunch	All Lunch
English Learners			
Male	3.74	3.78	3.77
Female	3.26	3.36	3.33
All Gender	3.55	3.62	3.60
English Only			
Male	4.25	3.75	3.99
Female	5.10	3.87	4.68
All Gender	4.67	3.79	4.28
All Language Status			
Male	4.11	3.77	3.90
Female	4.75	3.58	4.16
All Gender	4.42	3.70	4.01

Table 3: Aggregate Differences in Pre-Test CSA Averages

	M_{diff}	SE	z	p	d
Gender (F - M)	0.25	0.25	0.97	0.333	0.15
Language Status (EO - EL)	0.64	0.30	2.14	0.032	0.40
Economic Status (FP - FR)	0.77	0.25	3.15	0.002	0.48

8 RESULTS

8.1 Intersectional Differences in Pre-Test Scores

The pre-test performance of students displayed substantial heterogeneity across intersecting subgroups. Table 2 reports the average test scores for a reference group of first-grade students whose parents are High School Graduates and were assigned to the median teacher's classroom. The overall average reference score was 4.01 with a standard deviation of 1.60 that will be used to calculate Cohen's d to characterize the effect size of differences between intersecting groups. The table reveals substantial heterogeneity in performance across sub-groups, with the lowest average pre-test score generated by Female Language Learners with Full Pay lunch ($M = 3.26$, $SEM = 0.87$), which is 1.84 points lower than the highest average pre-test score of generated by Female English Only with Full Pay Lunch ($M = 5.10$, $SEM = 0.49$). The difference between these two groups is statistically significant with a large effect size ($M_{diff} = -1.84$, $SEM_{diff} = 0.79$, $z = 2.33$, $p < 0.02$, $d = 1.15$).

Characterizing the significance of the differences in Table 2 begins with a focus on differences between non-intersected groups. Table 6 reports the average difference, standard error, t-Statistic, the t-Statistic's p-Value against a two-sided alternative, and the normalized effect size for the difference. Socioeconomic status demonstrates a significant difference in student pre-test scores ($z = 3.15$, $p < 0.002$) with a medium effect size ($M_{diff} = 0.55$, $d = 0.48$). Language Status also demonstrates a significant difference ($z = 2.14$, $p < 0.032$) with a medium effect size ($M_{diff} = 0.64$, $d = 0.40$). Gender as an aggregate characteristic doesn't demonstrate significant differences ($z = 0.97$, $p < 0.333$) with a trivial effect size ($Mdiff = 0.25$, $d = 0.15$).

Table 4: Sub-Group Marginal Differences in CSA Reference Pre-Test Scores

	English Only - English Learners	Full Pay - Free/Reduced	Female - Male
English Learners		-0.013	-0.45
English Only		0.97^{***}	0.71^{***}
Full Pay	1.12^{**}		0.60
Free/Reduced	0.13		-0.19
Male	0.19	0.36	
Female	1.36^{***}	1.15^{***}	

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4 reports the average differences from table 6 for intersecting subgroups. Conditioning on language-status, English Learners don't demonstrate significant differences along either socioeconomic ($M_{diff} = -0.013$, $p < 0.974$) or gender ($M_{diff} = -0.444$, $p < 0.107$) categories while English Only students demonstrate significant differences across both socioeconomic ($M_{diff} = 0.97$, $p < 0.001$) and gender ($M_{diff} = 0.71$, $p < 0.001$) groups. Turning to socioeconomic status, students on a Full Pay lunch program show significant differences between language status ($M_{diff} = 1.12$, $p < 0.017$) but not significant gender differences ($M_{diff} = 0.60$, $p < 0.106$), whereas students on a free or reduced pay lunch demonstrate immaterial and insignificant differences by language status ($M_{diff} = 0.13$, $p < 0.607$) and gender ($M_{diff} = -0.19$, $p < 0.379$). Finally, considering gender differences, Females demonstrated significant differences in language status ($M_{diff} = 1.36$, $p < 0.001$) and socioeconomic status ($M_{diff} = 1.15$, $p < 0.001$) whereas Males demonstrated no such differences in language status ($M_{diff} = 0.19$, $p < 0.612$) or socioeconomic status ($M_{diff} = 0.36$, $p < 0.229$).

8.2 Outcomes of Curricular Intervention

To demonstrate that the curriculum improved student test scores, we analyze the post-test minus pre-test differences in student scores. Figure 1 presents a histogram of the post- minus pre-test scores, demonstrating a nearly uniform improvement in student performance. While one student's score dropped (by a single point) and another student's score was unchanged, the remaining 101 students all realized increases in their CSA test scores.

Figure 1: Histogram of CSA Post- Minus Pre-Test Scores

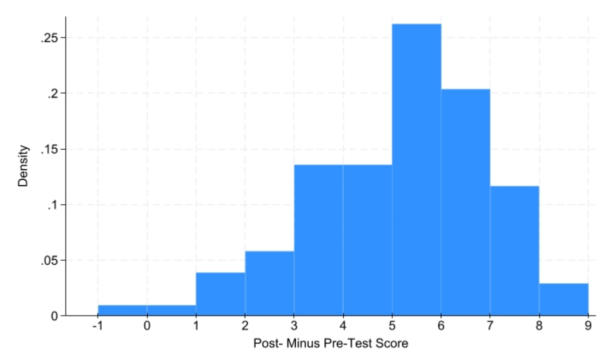

Table 5: CSA Post- Minus Pre-Test Average Reference Scores

	Full Pay Lunch	Free/Reduce Lunch	All Lunch
English Learners			
Male	4.14	3.58	3.71
Female	4.56	3.66	3.89
All Gender	4.31	3.61	3.78
English Only			
Male	3.57	4.00	3.79
Female	2.44	4.30	3.09
All Gender	3.01	4.10	3.49
All Language Status			
Male	3.72	3.78	3.76
Female	2.85	3.94	3.39
All Gender	3.30	3.84	3.61

Table 6: Aggregate Differences in Post- Minus Pre-Test CSA Average Reference Scores

	M_{diff}	SEM_{diff}	z	p	d
Gender (F - M)	-0.36	0.37	-0.98	0.333	-0.23
Language (EO - EL)	-0.28	0.34	-0.84	0.401	-0.18
Economic (FP - FR)	-0.66	0.28	-2.31	0.021	-0.41

There was a statistically significant difference between the mean pre-test scores and the mean post-test scores. Specifically, the pre-test scores had a lower mean ($M = 2.84$, $SD = 1.60$, $N = 103$) compared to the post-test scores ($M = 7.52$, $SD = 1.97$, $N = 103$). A paired-sample t-test revealed a t-statistic of 25.99, with $df = 102$ ($p < 0.001$). As the average score improvement was 4.69 points, the effect size was large, with a Cohen's d of 2.63.

Table 5 reports the average change in test scores for a reference group of first-grade students whose parents have a college-level education and were assigned to the median teacher's classroom. The overall change in the average reference score was 3.61, with the greatest change (4.56) being realized for Female Language Learners on a Full-Pay Lunch program and the smallest change (2.44) for Female Non-Language Learners in a Full-Pay Lunch Program.

The heterogeneity in the group average test score improvements counters the heterogeneity in group averages for the pre-test scores. The only significant difference appears for socio-economic status ($z = -2.31$, $p < 0.021$) with a medium effect size ($M_{diff} = -0.66$, $d = -0.41$). The differences in gender ($z = -0.98$, $p < 0.333$) and language status ($z = -0.84$, $p < 0.401$) aren't statistically significant and demonstrate trivial effect sizes.

8.3 Intersectional Convergence in Post-Test Scores

The post-test scores for students converged across the intersecting subgroups. Table 7 reports the average test scores for a reference group of first-grade students whose parents have a college-level education and were assigned to the median teacher's classroom. The overall average reference post-test score was 7.61 with a standard deviation of 1.97 ($M = 7.61$, $SD = 1.97$).

Table 7: Reference Post-Test CSA Average Scores

	Full Pay Lunch	Free/Reduce Lunch	All Lunch
English Learners			
Male	7.88	7.36	7.48
Female	7.82	7.02	7.22
All Gender	7.86	7.23	7.38
English Only			
Male	7.82	7.75	7.78
Female	7.54	8.17	7.76
All Gender	7.68	7.89	7.77
All Language Status			
Male	7.83	7.55	7.65
Female	7.60	7.51	7.56
All Gender	7.72	7.53	7.61

Table 8: Aggregate Differences in Post-Test CSA Averages

	M_{diff}	SEM_{diff}	z	p	d
Gender (F - M)	0.12	0.26	0.45	0.655	0.06
Language (EO - EL)	0.36	0.39	0.92	0.356	0.18
Economic (FP - FR)	0.12	0.22	0.53	0.598	0.06

Despite the increased variability in individual student performance from the pre-test ($M = 4.01$, $SD = 1.60$), the difference in average group post-test scores is less than that of the pre-test scores. Whereas the largest gap between group average scores on the pre-test was 1.97, the gap in group average scores on the post-test shrunk to 1.15. The lowest average post-test scores generated by Female Language Learners with Free/Reduced Lunch ($M = 7.02$, $SEM = 0.50$), is only 1.15 points lower than the highest average post-test score generated by Female English-Only students with Free/Reduced Lunch ($M = 8.17$, $SEM = 0.24$). This difference remains statistically significant with only a medium effect size ($M_{diff} = -1.15$, $SEM_{diff} = 0.46$, $p < 0.012$, $d = 0.72$). Excluding these two extremes, the differences among the remaining groups are not significant. The null hypothesis that all other intersecting group differences is zero is not rejected ($\chi^2(6, N = 103) = 11.63, p = 0.071$).

Table 8 reports no significant aggregate differences and trivial effect sizes along Gender ($M_{diff} = 0.12, SEM_{diff} = 0.26, p < 0.655$, $d = 0.06$), Language ($M_{diff} = 0.36$, $SEM_{diff} = 0.36$, $p < 0.356$, $d = 0.18$), and Socioeconomic Status ($M_{diff} = 0.12$, $SEM_{diff} = 0.22$, $p < 0.598$, $d = 0.06$).

Table 9 replicates the analysis for table 4 using post-test average scores. Notably, the range of differences in post-test average scores (range: $-0.280 - 0.659$) is much smaller than the range of differences in pre-test average scores (range: $-0.45 - 1.36$). Further, the only group difference that reaches the level of statistical significance is the contrast between Female English Only students and Female English Language Learners ($z = 1.95$, $p = 0.048$). The effect size for this difference is small ($M_{diff} = 0.495$, $d = 0.25$) and its statistical

Table 9: Sub-Group Marginal Differences in CSA Reference Post-Test Average Scores

	English Only - English Learners	FullPay - FreeReduce	Female - Male
English Learners		0.607	-0.255
English Only		-0.246	-0.027
Full Pay	0.659		-0.280
Free/Reduced	-0.194		-0.019
Male	0.268	0.263	
Female	0.495**	0.003	

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

significance would not survive any form of multiple-comparisons correction.

9 SIGNIFICANCE

In summary, pre-test scores for English Only students were significantly higher than for English Learners, though that difference is less significant for students on Free/Reduced meal programs and for Male students. Pre-test scores for students on a Full-Pay lunch program were significantly higher than for students on Free-Reduced Lunch, though that difference is less significant for English Learners and for Male students. While Gender Differences were not significant in aggregate, English-Only Female students do significantly outperform English-Only Male students.

From this baseline, the curricular intervention significantly increased students' CSA test scores. The greatest gains were associated with students from groups with initially lower average reference CSA pre-test scores, suggesting that the curriculum provided the support necessary to show gains for all students.

Finally, the post-test average reference scores were less variable across intersectional groups than the pre-test average reference scores. Very few inter-group differences were statistically significant and generated trivial to medium effect sizes.

The findings of this study carry significant implications for educational policy, particularly in the realm of early childhood computer science education. The Coding as Another Langauge curriculum has demonstrated notable success in enabling marginalized students, especially those with intersecting identities such as Latine and multilingual students from low-socioeconomic backgrounds, to bridge the achievement gap with their peers. This advancement calls for a broader exploration of the curriculum's potential benefits for similar student demographics.

Three accessible elements of the curriculum stand out as particularly supportive of diverse learners: the integration of coding and literacy, the use of storytelling, and the emphasis on collaboration. This study highlights culturally responsive programming through coding-literacy integration, particularly via storytelling. Writing and coding complement each other, enhancing learning in both domains [16, 46]. Collaboration further provided vital social support for students to participate in the curriculum and complete their ScratchJr projects. These findings will potentially inform future curricular refinement.

Taken together, these findings point to significant policy implications for early computer science education. The observed benefits of early computer science intervention are particularly noteworthy for young learners from historically marginalized and intersecting backgrounds. The data showing rapid improvement in students who initially had lower test scores strongly advocate for the implementation of targeted educational policies. These policies should aim to provide early and focused CS interventions in educational settings, especially for underrepresented and disadvantaged groups.

9.1 Implications for Policy

For policymakers, the examination of data from an intersectional perspective is paramount to promoting equity for marginalized students. By considering multiple overlapping social identities, such as race, language, and socioeconomic status, educational policies can be tailored to the multifaceted experiences of these students. Examining data from an intersectional perspective also ensures that policymakers understand how marginalization can be compounded by diverse group membership, paving the way toward allocating efforts and resources aimed at ameliorating systemic barriers. This approach ensures that interventions are specifically designed to support those at the intersections of various forms of marginalization. To this end, policymakers should prioritize funding and research for educational programs that adopt an intersectional approach, as this can lead to increased participation and inclusiveness for marginalized students while supporting equitable educational outcomes.

9.2 Limitations

There are several limitations to this study. First, there was no control group to compare pre-and post test scores. As this study is exploratory in nature, future research should aim to employ experimental studies to arrive at causal findings. Second, this study analyzes eight student subgroups with only 103 participants, resulting in some cells only having a small number of observations. Despite these limitations, the initial findings provide critical insights into the intersectional factors that influence K-2 students' computer science learning.

9.3 Conclusion

In conclusion, this study makes a significant contribution to the limited body of research on intersectionality in K-2 CS education. By demonstrating how student participation in the Coding as Another Language curriculum resulted in the reduction of educational disparities among K-2 students, predominantly from Latine and multilingual backgrounds with low-socioeconomic status, it highlights the importance of implementing evidence-based, culturally responsive programming in early CS education. Such initiatives are crucial in empowering students from diverse backgrounds, utilizing their unique resources and community assets, and facilitating their successful entry into the computing field. Consequently, the overarching implication for policy is the critical need for educational policymakers to not only invest in but also place a strong emphasis on culturally responsive, evidence-based curricula in early CS education, underscoring the importance of examining issues of intersectionality to ensure inclusivity and equity in addressing the diverse needs of young learners.

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