Technology Course-Taking in High School: Insights for Underrepresented Populations

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Abstract

In this study, we used multilevel logistic regressions to examine the impact of student- and school-level characteristics on three different HS course-taking outcomes: (a) any technology course; (b) any CS-focused technology course; and (c) any applied technology course. The analyses reveal that male and Asian students are more likely to enroll in technology courses regardless of type. Positive predictors of enrollment in applied technology courses were being Hispanic and attending a school with higher percentages of economically disadvantaged students. Importantly, even when CS-focused courses were available and MS CS was a requirement, enrollment disparities among underrepresented groups persisted. This suggests that the type of technology course significantly influences enrollment patterns and highlights the complex factors affecting access to CS education.

Background

Years of research on educational outcomes and opportunities have demonstrated that inequity in computer science (CS) is profound and widespread (NCES, 2019). Opportunities to learn in CS education are unevenly distributed, and students' experiences vary tremendously by race, ethnicity, socio-economic class, gender, and a myriad of other factors (Code.org, 2019). Despite major national and state efforts over the past 10 years, many groups have been systematically locked out of participation in CS education and CS careers (NASEM, 2024). The need to recruit and retain diverse students in CS is as high as ever (English, 2017; Madkins et al., 2019; Wiebe et al., 2019). In fact, the majority of public school students have not been exposed to any formal computer science education (CSE) prior to high school (HS; Gallup & Google, 2016).

There is no single pathway to CS learning and success. For many children and youth from underrepresented groups, CS pathways are fluid and dynamic as a function of learning opportunities both within and outside of school (NASEM, 2024). Many experience barriers to successful pathways, including course requirements, stigma and bias, low self-efficacy, and lack of out-of-school programs (Committee on STEM Education, 2018; Peckham et al., 2007). In addition, a major factor contributing to existing inequities is the acute shortage of stable and systematic CS course offerings and teachers who are adequately trained to deliver available CS curricula in K-12 education (Cuny, 2012; Leyzberg & Moretti, 2017; Montoya, 2017).

Providing CSE in middle school (MS) has been proposed as a strategy for addressing existing inequities, by engaging students at a time when their perceptions of gender roles and career trajectories are formed and as they actively plan for their high school and college education (Barker & Aspray, 2006; Wei et al., 2010). Additionally, research shows that improving CS curricula and cross-curricular integration of CS can help students from underrepresented populations recognize the intellectual and practical value of pursuing CSE (Estrada et al., 2016). Finally, without a clear CSE pathway, many traditionally underrepresented students in CS are effectively being pushed into pursuing non-technical/non-STEM career pathways (Denner, 2011).

In this study, we sought to examine the impact of student- and school-level characteristics on technology course-taking in high school. We used administrative data from several demographically diverse school districts in a northeastern state to assess the relative impact of student factors (e.g., gender, race, socioeconomic status, special education status) and school factors (e.g., CS as a requirement for middle school graduation; student body demographics) to course taking. The study's aim was to produce a more nuanced understanding of factors that influence technology course-taking by students from underrepresented groups.

Sample

Seven public school districts in a northeastern state provided administrative data from their middle and high schools that allowed us to examine the predictors of technology course enrollments in high school. We focused our analyses on students who: (a) graduated from high school in spring 2023, (b) had four full years of high school course enrollment data; and (c) had grade 8 achievement data. By narrowing our sample this way, we were able to focus on students who had four full years to opt in to technology courses and examine which personal and school-level characteristics were most closely related to technology course-taking in high school. We also excluded 12 students who reported as mixed race because of the small group size.

A total of 990 students with complete data met these inclusion criteria. If at any point during high school a student was classified as special education, English learner, economically disadvantaged, or chronically absent, we coded them as "Yes" on that particular variable for the purpose of analysis. We included an indicator for chronic absenteeism at any point during the four years of high school because chronic absenteeism has risen in the post pandemic years (Malkus, 2024). We lacked precise information on middle school course-taking, so as a proxy we included a dummy variable to indicate whether the student graduated from a middle school where a computer science class was required.

To test whether predictors of enrollment varied by course content, we reviewed high school course offerings and coded them as follows:

- *CS-focused* courses were those that focused more on theory, programming, robotics, and the creation of technology solutions
- *Applied technology* courses were those that focused more on the use of existing technologies in various settings (more akin to a vocational-style course)
- A *technology course* was identified as being either one of these two categories (which are mutually exclusive).

Characteristics of the sample are shown in **Table 1**.

Analyses

We conducted multilevel logistic regressions for three different high school course-taking outcomes: (a) any technology course; (b) any CS-focused technology course; and (c) any applied technology course. Given the nesting of students within schools, we first calculated the intra-class correlation coefficient (ICC) for each of the three outcomes. The guidelines for determining the use of multilevel modeling (MLM) are generally well defined, although the specific thresholds for its application can be subject to debate. Following Hox (2010), we interpreted ICCs of 0.05, 0.10, and 0.15 as small, medium, and large, respectively. For our study, the ICCs for the no predictor (null/empty model) model were 0.31, 0.21, and 0.45 for the respective outcomes, indicating a large school-level variability and justifying the use of multilevel models.

The model that we applied to each of these three outcomes included the following Level 1 (student) variables: gender, race (White as the referent group), special education, English learner, economic disadvantage, chronic absenteeism, and grade 8 GPA. Percent special education, economically disadvantaged, English learners and whether the student attended a middle school where CS was required were included at Level 2 (school). We added a variable that represented the percentage of all technology courses offered that are CS. Given our interest in understanding the factors that influence students' choices between different types of technology courses (i.e., CS-focused vs. applied technology), it was essential to control for the availability of CS courses.

Results

The results of the multilevel logistic regressions are presented in Error! Reference source not found.. Odds ratios greater than 1.0 indicate greater probability of taking a class (i.e., a positive effect), and odds ratios of 0.0 to 1.0 indicate lower probability of taking a class (i.e., a negative effect). An odds ratio of 1.0 can be interpreted as “no effect.” We also report Cohen’s d as another measure of effect size, along with 95% confidence intervals and p values.

Intraclass correlations ranged from 0.00 to 0.10. Note that all of the between-school variation in **applied technology course-taking** is captured by the four school-level predictors.

Marginal R^2 values (i.e., the proportion of variance explained by fixed effects) range from 0.270 to 0.461. Conditional R^2 values (i.e., the proportion of variance explained by both the fixed and random effects) range from 0.316 to 0.342.

Any Technology Course. Just over a quarter of the variance in HS technology course taking is explained by student characteristics (27%). Over a third of the variance is explained when school characteristics are included (34.2%). Being male, being Asian, and being in a school with a higher percentage of economically disadvantaged students had odds ratios that were greater than 1.0 and statistically significant, indicating that those characteristics were associated with an increased probability of taking a HS technology course. Being in a school with a higher percentage of English learners dramatically decreased the likelihood of taking a HS technology class. Additionally, the higher the percentage of technology courses offered that are CS, the greater the odds of students taking technology courses.

Any CS-Focused Technology Course. Similarly, slightly over a quarter of the variance in HS CS course taking is explained by student characteristics (28.9%). Nearly a third of the variance is explained when school characteristics are included (31.6%). Again, being male and being Asian were greater than 1.0 and statistically significant, indicating that those characteristics were associated with an increased probability of taking a HS CS course. Being in a school with a higher percentage of English learners dramatically decreased the likelihood of taking a HS CS class.

Additionally, the higher the percentage of technology courses offered that are CS, the greater the odds of students taking technology courses.

Any Applied Technology Course. Nearly half of the variance in applied technology course-taking was explained by student characteristics (46.1%). Being male, being Asian, being Hispanic, and being in a school with a higher percentage of economically disadvantaged students were greater than 1.0 and statistically significant, indicating that those characteristics were associated with an increased probability of taking an applied technology course. Being in a school with a higher percentage of English learners dramatically decreased the likelihood of taking an applied technology class. Again, the higher the percentage of technology courses offered that are CS, the greater the odds of students taking applied technology courses.

Discussion

We found that being male and being Asian were consistently positive predictors of technology course-taking, whether its focus was CS or applied technology. When we sought to unpack the reason why the school level factor, *percent economically disadvantaged* was a positive predictor of any technology course taking, we found that the effect was driven by enrollment in applied technology courses (e.g., IT essentials; financial and technology literacy). Indeed, when we narrowed our focus to the predictors of applied technology courses, *being Hispanic* was nearly as strong a positive predictor as being Asian.

The two main conclusions of these analyses are: (a) it is important to consider the type of technology courses that are available to students, and (b) even when CS-focused courses are offered in HS and even if MS CS was a requirement, the disparity in enrollments by underrepresented groups is unchanged.

The availability of applied technology courses seems to be an entry point to technology for students at economically disadvantaged schools and for Hispanic students. However, the question remains as to whether this decreases the technology enrollment gap or does this create a system that mirrors the college prep vs. vocational education tracks. A broader effort is needed to document how policies and practices contribute to inequities to guide systemic changes that can address gaps in opportunity, access, and quality of experience.

The persistent disparity in technology course enrollments by gender and race is sobering but unsurprising. Our team is currently working with the MS faculty and staff at the seven districts that provided us with these administrative data. By providing technical assistance designed to enhance the rigor and relevance of their MS CS courses, we hope to improve the course taking patterns of future cohorts of students.

In conclusion, equity in CS education is an ongoing process that requires intentional decision making and action toward addressing existing inequities. Given the specific contexts of different schools, districts, and communities, equity-related goals and strategies may be expected to vary from place to place and likely need to be adapted over time.

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Table 1. Sample Characteristics

Characteristic		HS 1 (N=196)	HS 2 (N=62)	HS 3 (N=115)	HS 4 (N=134)	HS 5 (N=312)	HS 6 (N=54)	HS 7 (N=118)	Total (N=991)
Gender	Female	98 (50.0%)	36 (58.1%)	57 (49.6%)	67 (50.0%)	160 (51.3%)	26 (48.1%)	61 (51.7%)	505 (51.0%)
	Male	98 (50.0%)	26 (41.9%)	57 (49.6%)	67 (50.0%)	152 (48.7%)	28 (51.9%)	57 (48.3%)	485 (48.9%)
Special Education (classified as SPED at any point during the four years of HS)	No	182 (92.9%)	59 (95.2%)	104 (90.4%)	100 (74.6%)	258 (82.7%)	41 (75.9%)	98 (83.1%)	842 (85.0%)
	Yes	14 (7.1%)	3 (4.8%)	11 (9.6%)	34 (25.4%)	54 (17.3%)	13 (24.1%)	20 (16.9%)	149 (15.0%)
Race	Asian	6 (3.1%)	1 (1.6%)	8 (7.0%)	1 (0.7%)	30 (9.6%)	0 (0%)	27 (22.9%)	73 (7.4%)
	Black	11 (5.6%)	8 (12.9%)	32 (27.8%)	37 (27.6%)	12 (3.8%)	9 (16.7%)	4 (3.4%)	113 (11.4%)
	Hispanic	168 (85.7%)	29 (46.8%)	69 (60.0%)	32 (23.9%)	48 (15.4%)	19 (35.2%)	44 (37.3%)	409 (41.3%)
	White	11 (5.6%)	24 (38.7%)	6 (5.2%)	64 (47.8%)	222 (71.2%)	26 (48.1%)	43 (36.4%)	396 (40.0%)
English Learner (classified as EL at any point during the four years of HS)	No	163 (83.2%)	61 (98.4%)	112 (97.4%)	126 (94.0%)	311 (99.7%)	53 (98.1%)	112 (94.9%)	938 (94.7%)
	Yes	33 (16.8%)	1 (1.6%)	3 (2.6%)	8 (6.0%)	1 (0.3%)	1 (1.9%)	6 (5.1%)	53 (5.3%)
Economically Disadvantaged	No	35 (17.9%)	33 (53.2%)	15 (13.0%)	41 (30.6%)	279 (89.4%)	20 (37.0%)	65 (55.1%)	488 (49.2%)
	Yes	161 (82.1%)	29 (46.8%)	100 (87.0%)	93 (69.4%)	33 (10.6%)	34 (63.0%)	53 (44.9%)	503 (50.8%)
Chronically Absent in HS (at any point during the four years of HS)	No	151 (77.0%)	54 (87.1%)	84 (73.0%)	69 (51.5%)	273 (87.5%)	41 (75.9%)	93 (78.8%)	765 (77.2%)
	Yes	45 (23.0%)	8 (12.9%)	31 (27.0%)	65 (48.5%)	39 (12.5%)	13 (24.1%)	25 (21.2%)	226 (22.8%)
Attended MS where CS was required?	Elective	0 (0%)	0 (0%)	0 (0%)	134 (100%)	312 (100%)	54 (100%)	0 (0%)	500 (50.5%)
	Required	196 (100%)	62 (100%)	115 (100%)	0 (0%)	0 (0%)	0 (0%)	118 (100%)	491 (49.5%)
Number of Technology Courses Taken in HS (at any point during the four years of HS)	0	104 (53.1%)	10 (16.1%)	25 (21.7%)	79 (59.0%)	168 (53.8%)	2 (3.7%)	80 (67.8%)	468 (47.2%)
	1	49 (25.0%)	16 (25.8%)	74 (64.3%)	38 (28.4%)	64 (20.5%)	34 (63.0%)	26 (22.0%)	301 (30.4%)
	2+	43 (21.9%)	36 (58.1%)	16 (13.9%)	17 (12.7%)	80 (25.6%)	18 (33.3%)	12 (10.2%)	222 (22.4%)
Number of CS Courses Taken in HS (at any point during the four years of HS)	0	113 (57.7%)	25 (40.3%)	98 (85.2%)	124 (92.5%)	229 (73.4%)	33 (61.1%)	106 (89.8%)	728 (73.5%)
	1	48 (24.5%)	18 (29.0%)	13 (11.3%)	7 (5.2%)	48 (15.4%)	19 (35.2%)	6 (5.1%)	159 (16.0%)
	2+	35 (17.9%)	19 (30.6%)	4 (3.5%)	3 (2.2%)	35 (11.2%)	2 (3.7%)	6 (5.1%)	104 (10.5%)
Number of Applied Technology Courses Taken in HS (at any point during the four years of HS)	0	186 (94.9%)	11 (17.7%)	28 (24.3%)	83 (61.9%)	205 (65.7%)	5 (9.3%)	89 (75.4%)	607 (61.3%)
	1	1 (0.5%)	51 (82.3%)	82 (71.3%)	42 (31.3%)	65 (20.8%)	49 (90.7%)	25 (21.2%)	315 (31.8%)
	2+	9 (4.6%)	0 (0.0%)	5 (4.3%)	9 (6.7%)	42 (13.5%)	0 (0.0%)	4 (3.4%)	69 (7.0%)

Note. One student had missing data on gender so analysis n=990.

Table 2. *Comparing Multilevel Logistic Regression Results for Different Target Variables*

Predictor	HS Course Taking Outcome											
	Any Technology Course				Any CS-Focused Technology Course				Any Applied Technology Course			
	Odds Ratio	Confidence Interval	p	Cohen's d	Odds Ratio	Confidence Interval	p	Cohen's d	Odds Ratio	Confidence Interval	p	Cohen's d
Fixed Effects												
Intercept	1.06	0.28 – 4.05	0.928	0.034	0.32	0.12 – 0.82	**0.018**	0.637	0.22	0.13 – 0.38	**<0.001**	0.837
Gender (1=male)	3.33	2.48 – 4.48	**<0.001**	0.664	3.85	2.73 – 5.42	**<0.001**	0.743	3.12	2.25 – 4.35	**<0.001**	0.628
Race – Asian (1=yes)	3.64	2.00 – 6.61	**<0.001**	0.712	3.77	2.00 – 7.09	**<0.001**	0.731	1.99	1.10 – 3.63	**0.024**	0.381
Race – Black (1=yes)	1.03	0.60 – 1.78	0.910	0.017	0.57	0.28 – 1.16	0.120	0.310	1.29	0.73 – 2.25	0.380	0.139
Race – Hispanic (1=yes)	1.50	0.97 – 2.31	0.070	0.222	0.94	0.57 – 1.55	0.801	0.036	1.71	1.09 – 2.66	**0.019**	0.294
Special Education (1=yes)	0.73	0.48 – 1.10	0.131	0.175	0.49	0.29 – 0.84	**0.009**	0.392	1.05	0.68 – 1.62	0.817	0.028
English Learner (1=yes)	0.99	0.53 – 1.86	0.975	0.006	0.96	0.47 – 1.96	0.914	0.021	0.90	0.37 – 2.20	0.818	0.058
Economically Disadvantaged (1=yes)	0.69	0.46 – 1.04	0.078	0.204	0.75	0.47 – 1.20	0.227	0.160	0.74	0.48 – 1.16	0.191	0.164
Chronically Absent, any time during HS (1=yes)	0.95	0.65 – 1.37	0.765	0.031	0.97	0.63 – 1.50	0.899	0.015	0.93	0.61 – 1.40	0.714	0.043
Grade 8 achievement (GPA)	0.86	0.72 – 1.03	0.111	0.083	0.87	0.71 – 1.06	0.162	0.080	1.08	0.86 – 1.34	0.505	0.041
Attended MS where CS was required (1=yes)	0.43	0.05 – 3.66	0.439	0.466	0.33	0.07 – 1.56	0.161	0.617	1.24	0.58 – 2.65	0.585	0.117
Percent Special Education	0.94	0.31 – 2.81	0.907	0.036	0.69	0.32 – 1.49	0.346	0.205	1.36	0.92 – 2.01	0.123	0.169
Percent Economically Disadvantaged	3.58	1.66 – 7.70	**0.001**	0.703	1.20	0.69 – 2.08	0.512	0.101	3.70	2.77 – 4.94	**<0.001**	0.721
Percent English Learners	0.18	0.08 – 0.42	**<0.001**	0.940	0.57	0.33 – 0.98	**0.043**	0.310	0.07	0.04 – 0.10	**<0.001**	1.503
Percent of All Tech Courses Offered that are CS	2.37	1.02 – 5.55	**0.046**	0.477	2.84	1.61 – 5.01	**<0.001**	0.576	2.47	1.72 – 3.54	**<0.001**	0.497
Random Effects												
σ^2	3.29				3.29				3.29			
τ_{00}	0.36				0.13				0.00			
ICC	0.10				0.04				-			
N schools	7				7				7			
N students	990				990				990			
Marginal R^2 / Conditional R^2	0.270 / 0.342				0.289 / 0.316				0.461 / NA			

Note. p-values in bold are statistically significant at $p \leq 0.05$