

Broadening participation and success in AP CS A

Predictive modeling from three years of data

Phillip A. Boda
The Learning Partnership
paboda@lponline.net

Steven McGee
The Learning Partnership
mcgee@lponline.net

ABSTRACT

The AP Computer Science A course and exam continually exhibit inequity among over- and under-represented populations. This paper explored three years of AP CS A data in the Chicago Public School district (CPS) from 2016-2019 (N = 561). We analyzed the impact of teacher and student-level variables to determine the extent AP CS A course taking and exam passing differences existed between over- and under-represented populations. Our analyses suggest four prominent findings: (1) CPS, in collaboration with their Research-Practice Partnership (Chicago Alliance for Equity in Computer Science; CAFÉCS), is broadening participation for students taking the AP CS A course; (2) Over- and under-represented students took the AP CS A exam at statistically comparable rates, suggesting differential encouragement to take or not take the AP CS A exam was not prevalent among these demographics; (3) After adjusting for teacher and student-level prior experience, there were no significant differences among over- and under-represented racial categorizations in their likelihoods to pass the AP CS A exam, albeit Female students were 3.3 times less likely to pass the exam than Males overall; (4) Taking the Exploring Computer Science course before AP CS A predicted students being 3.5 times more likely to pass the AP CS A exam than students that did not take ECS before AP CS A. Implications are discussed around secondary computer science course sequencing and lines of inquiry to encourage even greater broadening of participation in the AP CS A course and passing of the AP CS A exam.

CCS CONCEPTS

Social and professional topics ~Professional topics ~Computing education ~Computing education programs ~Computer science education

Social and professional topics ~Professional topics
~Computing education ~K-12 education

KEYWORDS

AP Computer Science; High School; Evaluation

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1 Introduction

As the population of the United States continues to diversify, our school systems have been charged with how we can also diversify the pathways and pipelines leading toward STEM and Computer Science (CS) careers. While early equity analyses have focused primarily on gender representation in CS and programming [9, 17, 27], more recent calls for equity in CS challenge the field to recognize the importance of the intersections between gender and race representations [23, 30]. Additionally, there has been a strong push to leverage the cultural affordances of diverse students' positional identities that could plausibly lead to ways of developing transformative and innovative initiatives to broaden participation and success in CS by drawing from social justice paradigms to think about the future of the field at K-12 grade levels [7, 37, 41].

Given the current state of the field, the focus on CS scope and sequence (as well as curriculum and pedagogy) has remained primarily at pre-Advanced Placement CS course levels. However, AP CS A course participation and exam success rates remain a prominent area of inquiry for equity initiatives and research studies. The focus on AP CS A, in turn, seeks to ameliorate who does and does not have the opportunity to experience high-quality and rigorous programming-specific learning in K-12. Given this area of interest, we sought to explore the following Research Questions related to AP CS A course taking and exam passing rates from three years of data in a large, urban midwestern city in the United States:

1. To what extent has Chicago Public Schools (CPS) been successful at broadening participation in the AP CS A course for under-represented populations in computer science?
 - a. What differences in prior school experiences are significant between over- and under-represented groups taking the AP CS A course?
2. What variables predict differences in AP CS A exam passing (i.e., college credit receiving; >3 score on the exam) rates among over- and under-represented populations in CPS?
 - a. What prior school experiences are significant predictors of AP CS A exam passing among these groups?

2 Background

There is a paucity of prior research exploring AP CS A course taking and exam passing, and with the onset of the new AP Computer Science Principles course leading the field as the lynchpin for equity in CS [8, 10, 40], such studies are still needed given the differences in the demographic makeup of students taking each course and the differences in these courses' curricular content [11, 21, 22]. Many studies examining such course taking and exam passing related to AP CS A are intervention-based studies that examine impact of designs to improve cognitive and/or affective outcomes leading to latent improvement in AP CS A exam passing, though sample sizes are small. However, these studies do not give an accurate picture of what equity in AP CS A looks like on larger scales in relation to work done that may involve Research-Practice Partnerships (RPP) to increase CS participation and success. This creates insufficient understandings of how and to what extent AP CS A, and other programming courses, become scaled at whole district levels to broaden participation among under-represented students in CS. Because there are few district-level analyses, the current field requires more studies on this scale that are useful when thinking about ameliorating inequity in the state of CS at a systems level, as well as who is being served best by those scaling efforts.

In terms of AP CS A course supplements and their impact on exam passing, one program in Georgia has showcased state- and district-focused attempts to broaden participation of under-represented populations in CS and increase rates of achieving credit-bearing status that is transferrable to post-secondary contexts from the AP CS A exam (>3 score), with promising results that such scaling of AP CS A is both possible and productive [12, 13]. This systemic support intervention model is laudable, especially as there still remains persistent inequity among under-represented populations across the United States that function at district, school, and teacher levels [11, 19, 26, 43]. However, to complicate this AP CS A/P landscape and its importance to college success in introductory computer science courses, a 2020 HLM analysis sampled over 2,700 college students to study the most impactful high school computer science content and pedagogy variables that predict higher grades in introductory computer science courses at the post-secondary level [2]. The data support the following:

When controlling for demographic and other factors, students who reported experiencing higher frequencies of coding practice in their most advanced HS CS course tended to receive higher grades in introductory college CS ... However, the positive effect of coding appears to apply only to those students who did not receive parental support in computing ... [moreover] none of our pedagogical predictor variables had significant ($p < .01$) interactions with gender, ethnicity, or race ... [and] having taken AP Computer Science A in HS [high school] — as opposed to a non-AP CS course — did not significantly predict grades in college CS.

This analysis presents an intriguing piece to the puzzle related to the impact of (1) broadening participation through more novel AP CS coursework, such as AP CS P, that doesn't provide extensive

coding exposure; (2) increasing CS success for under-represented students via outside-of-school initiatives; and (3) to what extent we may want to reconsider the interaction between AP CS A courses and what role they play in larger conversations about the purpose of CS at the K-12 level currently being researched [7, 37, 41].

Even given this backdrop of questioning the importance of AP CS A in terms of its relative impact toward students' pursuit and success in introductory computer science courses at the post-secondary level, inquiry into who participates in AP courses and the extent to which those populations are successful at achieving college credit at the high school level still remains a pertinent area of research across all disciplines [24, 26]. Indeed, the impact of AP coursework on undergraduate degree attainment is still a prevalent predictor to improve equitable participation and success across any disciplinary coursework beyond high school [1, 14, 38]. What is also of great importance when considering AP CS A course success is if, and how, prior experience with an introductory computer science course, such as Exploring Computer Science (ECS) [20, 36], may play a role in supporting an initial content groundwork presentation of CS from which AP CS A coursework could build upon to increase success in AP CS A exam passing. This background led to the current study researched and presented here.

3 Methods

This study used *Generalized Linear Modeling* (GLiM) techniques to predict any significant effects in relation to differences between over- and under-represented populations in AP CS A course taking (Research Question 1 and 1a), and then used this same statistical method to study the passing rates of the AP CS A exam (Research Question 2 and 2a). *Generalized Linear Modeling* (GLiM) is an alternative to *General Linear Modeling* (i.e., linear regression, ANOVA, etc...) that allows for non-normal dependent variable predictions (e.g., binomial, Gaussian, and Poisson count distributions), while also not requiring the stringent assumptions for traditional *General Linear Modeling* techniques [32]. Namely, GLiM permits additivity of effects, heteroscedasticity of data, and normality violations of residual errors. However, even given these liberal advantages of GLiM techniques, insufficient sampling sizes of covariate and categorical independent variables can still yield over-dispersed and inaccurate predictions in such models. To explore these smaller sampled relationships, we leveraged Fisher's Exact Tests of Independence [16], as this statistic allows for significance calculations of multi-leveled count variables to observe any difference in proportion that may be important to consider when making claims about any regression predictions.

In total, our population was 561 CPS high school students, and subsequent sampling of that population was used for our regression analyses presented in this paper. The analyses for both Research Questions drew from three years of data collected from CPS, a large urban district in the midwestern United States. The population data was collected as part of the Chicago Alliance for Equity in Computer Science RPP (CAFÉCS), which includes CPS. The samples for these analyses came directly from a data-sharing agreement containing student-level data for all CS students in that

school district. This level of student-aligned scores and other mediating factors provided the most accurate data set possible to test any hypotheses of differences that may exist among over- and under-represented demographics in AP CS A course taking and exam passing results, as well as account for any prior student and teacher experiences plausibly impactful for such analyses.

The variables used in these analyses included: (1) Students' AP CS A exam score clustered by credit-bearing status as a binary variable (pass, ≥ 3 score; not pass, <3); (2) Students' self-reported racial categorizations as a binary variable (i.e., Black + Hispanic students clustered together to codify under-represented student in CS; Asian + white students clustered to codify over-represented); (3) Gender as a binary variable (male/female); (4) Whether students took the introductory ECS course before AP CS A as a binary variable (yes/no); (5) Students' AP CS A course grade as a scale covariate variable; (6) The number of years a teacher taught AP CS A prior to the year a student took AP CS A with them as a scale covariate variable; and (7) Students' average course grade in their Intermediate Math courses as a scale covariate variable.

Students' Intermediate Math Course Grade was calculated by taking the average grade students received from one or both of the following Math courses that students took before taking AP CS A: Algebra 1 and Geometry. This inclusion of average Intermediate Math Course Grade was important, theoretically and pragmatically, given that decades-long evidence from research supports a strong connection between Math course grade/Mathematics aptitude and students' inevitable success in introductory post-secondary CS courses [2, 4, 25, 42, 44]. This inclusion of Intermediate Math Course grade, thus, also changes the sample sizes for the different regression models in that not all students that took AP CS A had previously taken this level of Math. When calculating the difference in samples of students who did and did not take intermediate math courses, there were no differences in gender proportions ($p \gg .05$); however, in racial proportions across both samples there were significant differences in representation ($p < .05$). Examined closer, differences emerged in relation to the excluded students not in the sample. These students who we did not have Intermediate Math course grades for had a higher proportion of Asian and white students, compared to our sample with almost equivalent sizes between over- and under-represented students across racial categorizations. This became a limitation to our study.

4 Outcomes

4.1 Research Question 1: Who is Taking AP CS A, and is there a Broadening of Participation in AP CS A within Chicago from 2016-2019?

The first outcome that was prominent from this analysis was that the district, in collaboration with CAFÉCS, is successfully broadening participation among demographic groups taking the AP CS A course, specifically Black and Hispanic female students. This section elaborates on the categorical analyses of independence and descriptive statistics found among these three years of data. As shown in Figure 1, the rate at which genders are taking the AP CS

A course over our three-year data set was relatively stable the first two years and grew significantly the third year. However, a Fisher's Exact Test of Independence showcases that the relative proportion of male to female students taking the course across these three years does not significantly change as a function of increasing the number of students across gender taking the AP CS A course ($p = .246$). Thus, in general, there remains an inequitable trend of more male students (~3-4 times more frequently) taking the AP CS A course than female students among schools in this district. This patterning over time was different, however, among racial categories of over- and under-represented students taking the AP CS A course.

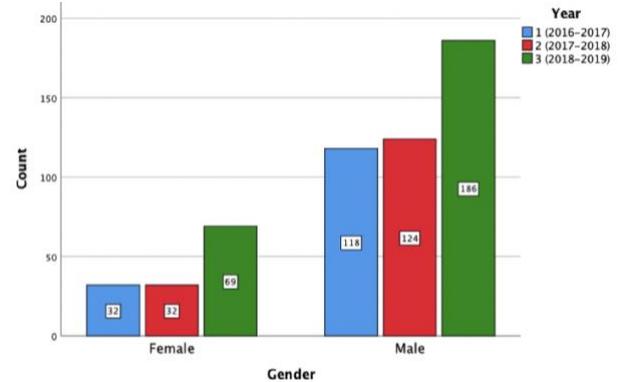


Figure 1. AP CS A course taking by gender over 3 years

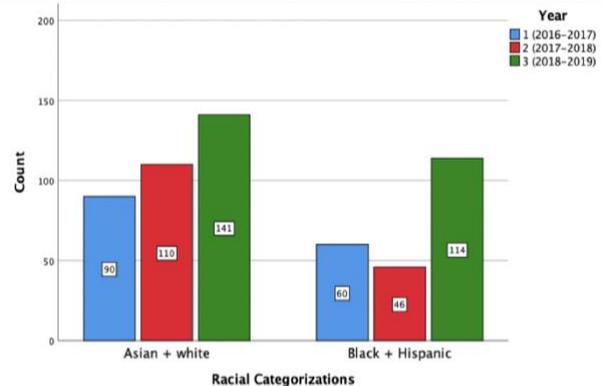


Figure 2. AP CS A course taking by race over 3 years

As shown in Figure 2, the rate at which different racial categorizations of students who represent over- and under-represented populations in Computer Science more broadly had changed over the three years for our data set. Between over- and under-represented students in our sample, the data suggests that there was a linear increase of Asian + white students over the three years, while the first two years for Black + Hispanic students showcase a general plateau of participation for taking the AP CS A course. This stagnancy of Black + Hispanic students taking the AP CS A course, however, rose significantly for the third year in our sample, which was also exemplified in the significant differences between the proportion of over- and under-represented students taking the AP CS A course found in a Fisher's Exact Test of Independence ($p = .009$). This statistic illuminates that Black + Hispanic students began gaining greater participation in the AP CS A course with the opportunity to take the AP CS A exam, and that

the differential proportions between over- and under-represented students who took AP CS A changed over time. The interaction between racial categorizations and gender across these three years in our sample also showcased that there was one specific population that might be gaining the greatest participation to AP CS A.

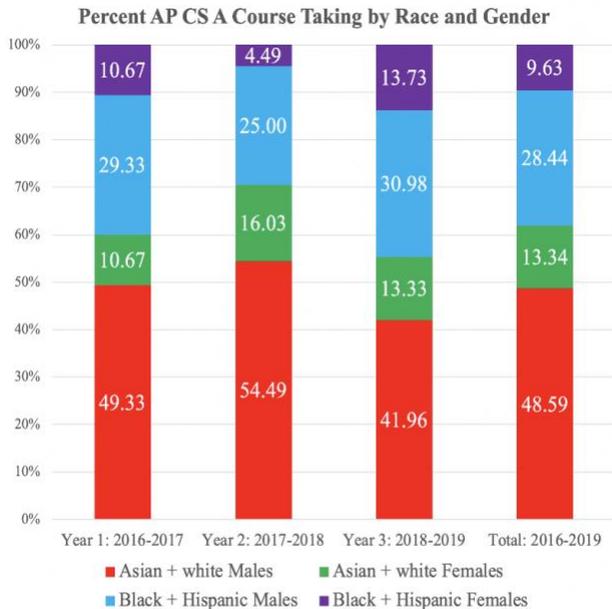


Figure 3. AP CS A course taking by race and gender

In Figure 3, the rates of different racial categorizations and genders that took the AP CS A course were relatively stable across our data. We conducted Fisher’s Exact Tests to confirm these hypotheses, which suggest no significant differences in terms of the proportions among racial categorizations and their interaction with gender over the three years, or as a Total: Year 1 ($p = .22$); Year 2 ($p = .38$); Year 3 ($p = .26$); Total ($p = .26$). However, when taken as a whole (Column 4, Total: 2016-2019), there seems to be a higher female-male ratio between under-represented students than their over-represented counterparts (Over-represented = $13.3/48.6 = 0.27$ Female; Under-represented = $9.63/28.44 = 0.34$ Female). This suggests that while the general trends among race and gender interactions do not seem to change significantly over time in terms of who is taking the AP CS A course, the combined data set showcases that Black + Hispanic female students are more represented in AP CS A course taking in relation to their male racial counterparts, specifically compared to Asian + white female-male ratios. However, the number of female students overall taking AP CS A remain low (~23%). We further explore the significance of this difference in a subsequent binomial logistic regression model.

4.2 Research Question 1a: Analyzing Significant Differences of Prior Academic Experience and AP CS A Course Taking among Under- and Over-Represented Students in Chicago

Building off of the previous section that analyzed the categorical and descriptive statistics alluding to CPS having success in

broadening participation among under-represented demographic groups taking the AP CS A course, this section leverages predictive statistics to give a robust analytic approach and support to this claim. This section also presents the second prominent result that AP CS exam taking rates among over- and under-represented populations were not different after covariate adjustment. To determine the extent to which under- and over-represented students had differences between our clustered racial categorizations in relation to broadening participation and equivalent AP CS A exam taking rates, we first used GLiM via Binomial Logistic Regression modeling parameters with the dependent binary values being Asian + white students within one category (used as referent; over-represented students) and Black + Hispanic students as the target comparison group (under-represented students in AP CS A).

Our final sample size out of the possible 561 students in our population was 466, which was less than the total population, to reiterate, because not all students took an Intermediate Math Course before they took AP CS A. Below in Table 1 are the GLiM binomial regression results comparing under- to over-represented students. The dependent variable in this model was racial category with the referent group being Asian + white students (over-represented) and the comparison estimates (shown in Table 1) represents if and to what extent under-represented students (Black + Hispanic) differ significantly from their over-represented counterparts, if at all.

Table 1
Parameter estimates: Under-represented students

	B	Std. Error	Exp(B)
(Intercept)	2.68***	0.67	14.61
Student Absences	0.02	0.01	1.02
Math Interim. Avg. Grade	-0.85***	0.16	0.43
Years Teaching AP CS A	-0.13*	0.05	0.88
[Student Gender]	0.45	0.24	1.56
[Took ECS Before AP]	0.45*	0.23	1.59
[Took AP CS A Exam]	0.09	0.36	1.10

* $p < .05$; *** $p < .001$

We controlled for student absences ($p = .066$), students’ intermediate Math course grade ($\beta = -.085$; $p < .000$; Exp [β ; Black + Hispanic] = .4), and educator’s number of years teaching AP CS A ($\beta = -.13$; $p = .01$; Exp [β] = .9). This alluded to Black + Hispanic students being awarded 2.3 times lower grades in their intermediate Math courses than their Asian + white counterparts. Moreover, the covariate results also alluded to Black + Hispanic students being 1.1 times less likely to have a teacher with one or more years of experience previously teaching AP CS A, which will be shown to be important later in terms of what impacts AP CS A exam passing.

For our categorical independent variables, we explored differences related to gender ($p = .06$), whether students took the introductory ECS course before taking AP CS A ($\beta = .45$; $p = .045$; Exp [β ; Black + Hispanic] = 1.6), and whether student groups took the AP CS A exam at comparable rates ($p = .8$). These categorical independent variable comparisons, after covariate adjustment, suggest that Black + Hispanic students are 1.6 times more likely to take ECS before they take the AP CS A course than their Asian + white counterparts ($p = .045$); though, no differences exist between racial categories among AP CS A Exam taking rates ($p = .79$).

These course taking results suggest, when combined with our longitudinal observations of the frequency of Black + Hispanic males and females taking AP CS A provided above, that there are growing rates of broadened participation in AP CS A for under-represented students. There also is a significantly higher likelihood for Black + Hispanic students to take the ECS course before they take AP CS A, which became a factor important in our modeling of passing rates below. However, Black + Hispanic students are less likely to have an educator with prior experience teaching AP CS A, which is also important in our AP CS A exam passing analyses.

Given that we could not disaggregate the interaction between these two racial categorizations and the genders present therein within this GLiM modeling due to insufficient sample sizes in these interactions, we used Fisher's Exact Tests of Independence to determine any further differences related to our categorical variables. For ECS taking rates, when disaggregated among racial categorizations and genders, there were no differences in who did not take ECS ($p = .439$) or who did take ECS (.411). There were also no differences among these race and gender interactions in terms of who didn't take the AP CS A exam ($p = 1.00$) and who did take the AP CS A exam ($p = .232$). These results are combined with a binomial logistic regression model to further explore the passing rates of under- and over-represented students in the next section.

4.3 Research Question 2 and 2a: Predictive Differences in AP CS A Exam Passing Rates among Over- and Under-Represented Students

The final two pertinent findings presented here are specific to AP CS A passing rates among over- and under-represented populations, as well as the impact of taking ECS on AP CS A exam passing. To determine the extent to which there were differences among over- and under-represented populations passing the AP CS A exam, we again used GLiM via Binomial Logistic Regression modeling parameters with the dependent variable for this model being students who passed the AP CS A Exam (received a 3 or higher; used as target) compared to students that did not pass the AP CS A Exam (received a 1 or 2; used as referent category). 506 out of the possible 561 students took the AP CSA exam; of those 506, 412 were included in this model due to sampling for students that took one or more Intermediate Math courses before AP CS A. Below in Table 2 are these GLiM binomial regression results.

Table 2
Parameter estimates: AP CS A Exam Passing

	B	Std. Error	Exp(B)
Intercept	-3.79***	0.76	0.02
Math Intern. Avg. Grade	1.32***	0.22	3.74
Years Teaching AP CS A	0.31***	0.06	1.36
[Student Race]	-0.75	0.51	0.47
[Student Gender] = Male	1.19*	0.58	3.30
[Took ECS Before AP]	1.26*	0.50	3.53
[Course Grade]	-0.05	0.51	0.95
[Student Race] * [Course Grade]	0.94	0.53	2.55
[Student Gender] * [Course Grade]	0.26	0.59	1.30
[Student Race] * [Took ECS Before AP]	0.93	0.54	2.53
[Student Gender] * [Took ECS Before AP]	0.28	0.60	1.33
[Took ECS Before AP] * [Course Grade]	1.05	0.53	2.85

* $p < .05$; *** $p < .001$

We controlled for students' Intermediate Math Course grade ($\beta = 1.32$; $p < .000$; Exp [β] = 3.7) and the number of years' experience the teacher had teaching the AP CS A course ($\beta = .31$; $p < .000$; Exp [β] = 1.3). These covariates alluded to the importance of students' prior Math performance as being a predictor of success in passing AP CS A (i.e., increasing your Intermediate Math Grade by 1 letter grade predicted a 3.7 times greater likelihood to pass the AP CS A exam). These data also suggest that students that had a teacher that previously taught AP CS A increases their chances of passing the AP CS A exam by 1.3 times for each year this instructor taught the AP CS A course. These student and teacher-level covariates, therein, adjust all subsequent variable predictions in the model.

For one of our categorical independent predictive variables, we explored differences related to racial categorizations we previously used in the above GLiM model (Black + Hispanic; Asian + white), which, after covariate adjustment, showcased no differences in passing rates for the AP CS A exam ($p = .142$). Other categorical variables included gender ($\beta = 1.2$; $p = .041$; Exp [β ; Male] = 3.3), whether students took the introductory ECS course before taking the AP CS A exam ($\beta = 1.2$; $p = .013$; Exp [β ; If Took ECS] = 3.5), and whether students received an A or below an A in the AP CS A course ($p = .9$). This latter categorical variable was included given that 58.8% of students who took the AP CS A course in our sample ($N = 561$) received an A. Of those students who received an A or below an A there were significant differences between our racial categorizations (Asian + white students received an A grade 2.2 times more often than Black + Hispanic students; Fisher's Exact Test of Independence: $p < .000$). These main effects alluded to no differences in passing rates among racial categorizations that are characterized by over- and under-represented populations in CS; however, there still remained a gendered differential effect of passing whereby Female students were 3.3 time *less likely* to pass the AP CS A exam after adjusting for prior Math performance and teacher experience. Of positive note, students that took ECS before AP CS A were 3.5 times *more likely* to pass the AP CS A exam than those who did not, after covariate adjustment, alluding to the importance of the introductory computer science course ECS in preparing students for the AP CS A scope and sequence.

Further interaction effects between some categorical independent variables were included in the regression model due their sufficient sampling sizes. Those interactions included: Racial categorizations by AP CS A course grade ($p = .080$); gender by AP CS A course grade ($p = .663$); racial categorizations by whether they took ECS before AP CS A ($p = .085$); gender by whether they took ECS before AP CS A ($p = .636$); and AP CS A course grade by whether they took ECS before AP CS A ($p = .052$; Exp [β] = 2.8). Given all of these interaction effects being insignificant, the model alluded to the importance of ECS and its impact on students passing the AP CS A exam to be homogenously applicable across racial categorizations and genders. This modeling led to an investigation of multi-layered Fisher's Tests of Independence to test if there were significant differences among racial categorizations and genders within this and other interactions that could explore relationships of passing the AP CS A exam not sufficiently sampled for predictive quality within our GLiM model.

Of first exploration, Fisher's Tests of Independence for racial categorizations by gender to determine differences in AP CS A exam passing and not passing rates were conducted. There were no significant differences in terms of the proportion of students by racial categories and gender who passed ($p = 1.00$) or did not pass ($p = .280$) the AP CS A exam, albeit there were more Asian + white students that passed the exam (as an overall sum) when compared to Black + Hispanic students. However, this may be explained partially by the sample being 63.2% Asian + white students. This data corroborates the above results of no differences among passing rates related to racial categorizations and their gender interactions.

Our next interaction exploration sought to test if any differences existed among racial categorizations by gender and also if ECS was taken before the AP CS A course to examine if any differential proportions existed in passing rates of students. All interaction effects for these Fisher's Exact Tests of Independence were insignificant ($p > .05$). A similar set of tests for interaction effects among racial categorizations by gender were conducted in relation to the proportion of students who received an AP CS A course grade of A or below A, and if those proportions were significantly different in relation to the probability to pass the AP CS A exam. All of these interaction effects were also insignificant ($p \gg .05$). Given these additional Tests of Independence for the categorical interaction impacts unable to be input into the regression model due to insufficient sample sizes, we can further conclude that our original model is our best predictive analysis for this data. In turn, the data supports that there are areas of equitable participation and success among under-represented populations in AP CS A for CPS, as well as areas for which there should be greater prioritization to further ameliorate inequity among these populations and work toward broadening participation and exam success in AP CS A.

5 Discussion

At first glance, some of the findings we have presented here are undoubtedly expected, and others intriguing for future inquiries. For our first Research Question, in terms of AP CS A course participation, given that the CAFÉCS team has spent years developing their relationship with CPS to improve and broaden participation among under-represented populations in CS by expanding ECS throughout the district, and the CPS School Board enacting a high-school CS graduation requirement, it was hopefully expected that such an expansion might lead to greater AP CS course taking among under-represented populations. Given this expansion of ECS supported by both the work of the RPP and the district that began in 2012, as well as accelerated in 2016 due to the imposed graduation requirement (Year 1 of the data here), it is plausible that by 2018-2019 (Year 3 of this data) exposing more students to ECS can be partially attributed to this broadening of participation among Black + Hispanic young men and women. This patterned growth was seen in both of our descriptive and predictive models.

Within these models (Tables 1 and 2), though, there still remains evidence of more broad systemic inequities related to other courses connected directly to CS success such as Intermediate Math course grades being significantly less for Black + Hispanic students,

as well as this under-represented population being taught by CS instructors with significantly less prior experience implementing the AP CS A course material. However, Black + Hispanic students were significantly more likely to take the introductory ECS course than their Asian + white counterparts, which, when combined with the AP CS A passing analysis (Table 2), discussed below, sheds light on plausible ways to ameliorate inequitable participation and success found in AP CS A research in the past [12, 13, 43].

One surprising predictor for passing the AP CS A exam was whether a student took the introductory ECS course before they took the AP CS A course. This is a highly impactful contribution to the CS field, specifically in the face of advocates against such 'non-programming specific CS courses' [15, 35] and recent predictions on the importance of coding to influence post-secondary CS course success [3]. However, given recent research analyzing ECS's impact toward increasing the development of programming expertise among students who took the course [33], a connection between ECS and AP CS A is not far-fetched. Indeed, the predictive models for AP CS A exam passing did exhibit the importance of more systemic changes needed broadly across curriculum such as Intermediate Math Course success and the persistence of gender gaps in CS seen for decades [9, 17, 19, 27, 43], but also shed light on the equivalent passing rates across Black + Hispanic and Asian + white racial categorizations. These results, in sum, suggest that during this school district's attempts to broaden CS participation among under-represented populations that students from races not proportionally represented in CS more broadly were served well by this scaling and were not 'left in the shallow end' [28].

6 Conclusion

With a lineage of research over twenty years showcasing multiple dimensions that decrease female participation, interest, aspiration, and success in CS at the K-12 and post-secondary levels [5, 6, 18, 29, 31, 34, 39], the findings presented here on the persistence of gender disparity are disconcerting, indeed. The data also suggests, though, that racial disparities are plausibly ameliorated when AP CS A was scaled in Chicago, and that there are preliminary courses that can improve success on the AP CS A exam (i.e., ECS). These findings can advise district leaders to use evidence to make CS policy decisions to support students that need it the most. Most notably by leveraging ECS as a foundational CS course to decide when a school may be ready for the implementation of AP CS A, as well as to think more acutely about how intermediate CS courses could be developed to support a scope and sequence of CS courses starting with ECS and continuing through AP CS courses.

In the end, the results we present here encourage future analyses that explore student trajectories across K-12 CS courses available in Chicago and beyond to describe more causal links that support under-represented students to take the AP CS A course and pass the AP CS A exam. Finally, such inquiries should also include if and how AP CS P could live up to its intention in order to spark interest and build capacity for all students to succeed in CS [8, 10, 40]. This leaves future inquiries with more questions than answers but allows for hopeful predictions for the future of K-12 CS and AP CS A.

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REFERENCES

- [1] Jonathan J. Beard, Julian Hsu, Maureen Ewing, and Kelly E. Godfrey. 2019. Studying the relationships between the number of APs, AP performance, and college outcomes. *Educational Measurement: Issues and Practice*, 38, 4, 42-54.
- [2] Susan Bergin and Ronan Reilly. 2005. Programming: Factors that influence success. In *Proc. ACM Tech. Sym. Comp. Sci. Ed.*, 411-415.
- [3] Heidi Burgiel, Philip M. Sadler, and Gerhard Sonnert. 2020. The association of high school computer science content and pedagogy with students' success in college computer science. *ACM Trans. Comp. Ed.*, 20, 2, 1-21.
- [4] Patricia F. Campbell and George P. McCabe. 1984. Predicting the success of freshmen in a computer science major. *Communications of the ACM*, 27, 1108-1113.
- [5] Coleen M. Carrigan. 2017. Yearning to give back: Searching for social purpose in computer science and engineering. *Frontiers in Psychology*, 8, 1178.
- [6] Sapna Cheryan, Benjamin Drury, and Marissa Vichayapai. 2013. Enduring influence of stereotypical computer science role models on women's academic aspirations. *Psychology of Women Quarterly*, 37, 1, 72-79.
- [7] Laquana Cooke, Sara Vogel, Michael Lachney, and Rafi Santo. 2019. Culturally responsive computing: Supporting diverse justice projects in/as computer science education. In *Proc. Research on Equity and Sustained Participation in Engineering, Computing, and Technology (RESPECT)*, 1-2. IEEE.
- [8] Jan Cuny. 2015. Transforming K-12 computing education: AP computer science principles. *ACM Inroads*, 6, 4, 58-59.
- [9] Suzanne K Damarin. 1989. Rethinking equity: An imperative for educational computing. *Computing Teacher*, 16, 7, 16-18.
- [10] Lien Diaz, Frances P. Trees, Dale Reed, Richard Kick, and Andrew Kuemmel. 2017. Social justice and equity in CS education: Inaugural launch of AP Computer Science Principles. In *Proc. ACM Tech. Sym. Comp. Sci. Ed.*, 653-654.
- [11] Barbara J. Ericson and Mark Guzdial. 2014. Measuring demographics and performance in computer science education at a nationwide scale using AP CS data. In *Proc. ACM Tech. Sym. Comp. Sci. Ed.*, 217-222.
- [12] Barbara J. Ericson, Miranda C. Parker, and Shelly Engelman. 2016. Sisters Rise Up 4 CS: Helping female students pass the advanced placement Computer Science A exam. In *Proc. ACM Tech. Sym. Comp. Sci. Ed.*, 309-314.
- [13] Barbara J. Ericson, and Tom McKlin. 2018. Helping underrepresented students succeed in AP CS A and beyond. In *Proc. ACM Tech. Sym. Comp. Sci. Ed.*, 356-361.
- [14] Brent J. Evans. 2019. How college students use advanced placement credit. *American Educational Research Journal*, 56, 925-954.
- [15] Steven Fink. 2020. Don't rely on cute apps and games to teach coding: Turn to your students instead. *EdSurge* (Jan 18, 2020).
- [16] Ronald A. Fisher. 1922. On the interpretation of χ^2 from contingency tables, and the calculation of P. *Journal of Royal Stat. Soc.* 85, 1, 87-94. doi:10.2307/2340521
- [17] Karen A. Frenkel. 1990. Women and computing. *Comm. ACM*, 33, 11, 34-46.
- [18] Jonathon Andrew Good. 2018. *Gender-related effects of advanced placement computer science courses on self-efficacy, belongingness, and persistence*. Dissertation. Michigan State University.
- [19] Joanna Goode. 2007. If you build teachers, will students come? The role of teachers in broadening computer science learning for urban youth. *Journal of Educational Computing Research*, 36, 1, 65-88.
- [20] Joanna Goode, Gail Chapman, and Jane Margolis. 2012. Beyond curriculum: The exploring computer science program. *ACM Inroads*, 3, 2, 47-53.
- [21] Douglas D. Havard and Keith E. Howard. 2019. All Advanced Placement (AP) computer science is not created equal: A comparison of AP Computer Science A and Computer Science Principles. *Journal of Computer Science Integration*, 2, 1, 16-34.
- [22] Keith E. Howard, and Douglas D. Havard. 2019. Advanced Placement (AP) Computer Science Principles: Searching for equity in a two-tiered solution to underrepresentation. *Journal of Computer Science Integration*, 2, 1-15.
- [23] Nwannediya Ada Ibe, Rebecca Howsmon, Lauren Penney, Nathaniel Granor, Leigh Ann DeLyser, and Kevin Wang. 2018. Reflections of a diversity, equity, and inclusion working group based on data from a national CS education program. In *Proc. ACM Tech. Sym. Comp. Sci. Ed.*, 711-716.
- [24] Sunéal Kolluri. 2018. Advanced Placement: The dual challenge of equal access and effectiveness. *Review of Educational Research*, 88, 671-711.
- [25] Amruth N. Kumar. 2018. Predicting student success in computer science—a reproducibility study. In *IEEE Frontiers in Education Conference*, pp. 1-6.
- [26] Kip Lim, and Colleen Lewis. 2020. Three metrics of success for high school CSforAll initiatives: Demographic patterns from 2003 to 2019 on Advanced Placement computer science exams. In *Proc. ACM Tech. Sym. Comp. Sci. Ed.*, 598-604.
- [27] Marcia C. Linn. 1985. Fostering equitable consequences from computer learning environments. *Sex Roles*, 13, 3-4, 229-240.
- [28] Jane Margolis. 2008. *Stuck in the shallow end: education, race, and computing*. The MIT Press, Cambridge.
- [29] Jane Margolis and Allen Fisher. 2003. *Unlocking the clubhouse: Women in computing*. The MIT Press, Cambridge.
- [30] Jane Margolis, Joanna Goode, and Gail Chapman. 2015. An equity lens for scaling: a critical juncture for exploring computer science. *ACM Inroads*, 6, 3, 58-66.
- [31] Allison Master, Sapna Cheryan, and Andrew N. Meltzoff. 2016. Computing whether she belongs: Stereotypes undermine girls' interest and sense of belonging in computer science. *Journal of Educational Psychology*, 10, 424-437.
- [32] Peter McCullagh and John A. Nelder. 1989. *Generalized Linear Models* (Vol. 2). CRC Press.
- [33] Steven McGee, Ronald I. Greenberg, Randi McGee-Tekula, Jennifer Duck, Andrew M. Rasmussen, Lucia Dettori, and Dale F. Reed. 2019. An examination of the correlation of Exploring Computer Science course performance and the development of programming expertise. In *Proc. ACM Tech. Sym. Comp. Sci. Ed.*, 1067-1073.
- [34] Thomas J. Misa. Ed. 2011. *Gender codes: Why women are leaving computing*. John Wiley & Sons.
- [35] Scott R. Portnoff. 2020. A new pedagogy to address the unacknowledged failure of American secondary CS education. *ACM Inroads*, 11, 2, 22-45.
- [36] Jean J. Ryoo, Jane Margolis, Clifford H. Lee, Cueponcaxochitl DM Sandoval, and Joanna Goode. 2013. Democratizing computer science knowledge: Transforming the face of computer science through public high school education. *Learning, Media and Technology*, 38, 161-181.
- [37] Rafi Santo, Sara Vogel, Jean Ryoo, Jill Denner, Camie Belgrave, Alicia Moriss, and Alex Tirado. 2020. Who has a seat at the table in CSed? Rethinking equity through the lens of decision-making and power in computer science education initiatives. In *Proc. ACM Tech. Sym. Comp. Sci. Ed.*, 329-330.
- [38] Jonathan Smith, Michael Hurwitz, and Christopher Avery. 2017. Giving college credit where it is due: Advanced Placement exam scores and college outcomes. *Journal of Labor Economics*, 35, 1, 67-147.
- [39] Heinrich Stumpf and Julian C. Stanley. 1997. The gender gap in Advanced Placement computer science. *College Board Review*, 181, 22-27.
- [40] Paul T. Tymann, Fran P. Trees, Lester Wainwright, Richard Kick, Sandy Czajka, Andrew Kuemmel, and Lien Diaz. 2015. Achieving a shared goal with AP Computer Science A and AP Computer Science Principles. In *Proc. ACM Tech. Sym. Comp. Sci. Ed.*, 436-437.
- [41] Sepehr Vakil. 2018. Ethics, identity, and political vision: Toward a justice-centered approach to equity in computer science education. *Harvard Educational Review*, 88, 1, 26-52.
- [42] Philip R. Ventura Jr. 2005. Identifying predictors of success for an objects-first CS1. *Computer Science Education*, 15, 223-243.
- [43] Jennifer Wang, Hai Hong, Jason Ravitz, and Sepehr Hejazi Moghadam. 2016. Landscape of K-12 computer science education in the US: Perceptions, access, and barriers. In *Proc. ACM Tech. Sym. Comp. Sci. Ed.*, 645-650.
- [44] Brenda Cantwell Wilson. 2002. A study of factors promoting success in computer science including gender differences. *Computer Science Education*, 12, 141-164.