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Gender Differences in the Pathway from Application through Graduation in a Computer Science Major

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Abstract

It is well-established that women are underrepresented in computer science (CS) education, but less is known about their representation at key university stages—application, admission, and retention through graduation. This study addresses that gap by investigating three research questions: (1) How do the distributions of women and men who *apply* to CS differ? (2) How do the distributions of women and men *admitted* to CS differ? (3) How do the distributions of women and men *retained to graduation* in CS differ? Using ten years of data from four U.S. institutions with varied demographics and characteristics, we apply a data-intensive approach combining descriptive statistics, visualizations, and regression modeling. Our findings reveal gender imbalances at the application stage, partial mitigation at admission, and similar retention rates but different outcomes for non-retained students by gender. We also find institutional differences, with more competitive schools showing larger gender gaps, while smaller private institutions show smaller disparities. Our results underscore the need to focus earlier in the pathways. Attracting more women to apply to college CS programs is essential for narrowing the gender gap, and high school exposure to CS alone might not be enough to spark sustained early interest.

CCS Concepts

• **Social and professional topics** → **Computing education programs**.

Keywords

Computer Science Pathways, Higher Education, Gender, Application, Admittance, Retention

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1 Introduction

Computer Science (CS) jobs are vital to the global economy's growth. Over the past decade, demand for CS-educated professionals has surged and continues to rise. Software development—one of the most common CS career paths—is projected to grow 26% from 2023 to 2033, ranking eighth in the number of new jobs expected [61]. U.S. colleges and universities¹ have seen record-high CS major enrollments over the past 5–10 years [19]. In response, many CS departments now restrict access to their courses or major, limiting enrollment for both incoming students and those seeking to switch [19]. These admission policies can significantly impact access and equity.

CS is one of the most gender-skewed STEM fields [30, 84], with women making up only 21% of degree recipients, lower than any other STEM discipline except Engineering (considered here as one field) [31]. This underrepresentation stems from multiple stages of the CS pathways [18, 50]. Gender stereotypes discourage girls from pursuing computing well before college [51, 52], and girls take high school CS courses at significantly lower rates than boys [27, 42]. Later, competitive college CS admission policies can undermine women's sense of belonging and deter them from pursuing the field [60, 74]. Once in college, negative experiences often drive women away from CS [8, 9, 15, 40, 80]. Workforce culture further reduces female participation, with fewer women entering computing jobs and more leaving them compared to men [50, 76, 79].

While the broad pattern of gender underrepresentation in computing is well known, less is understood about specific transitions within the CS pathway, especially at the university level. Our focus is on the pathway into, through, and out of university CS programs. Few studies explore how gender affects application and admission decisions when controlling for other variables. As noted by

¹We use "college" and "university" interchangeably to refer to institutions offering undergraduate and/or graduate degrees.

Stephenson et al. (2018), most existing datasets focus on graduation outcomes and lack the granularity needed to analyze student pathways within CS programs [75].

This study addresses gaps in the literature by taking a data-rich approach to examining students' progression into, through, and out of the undergraduate CS major. We examine gender distributions at three key transition points in the pathway: application, admission, and graduation, using ten years of data from four U.S. institutions that vary in size, type (three public, one private), demographics, focus, and selectivity. Using this rich longitudinal data set, we explore the following research questions:

RQ1: How do the distributions of men and women who *apply* to CS differ?

RQ2: How do the distributions of men and women *admitted* to CS differ?

RQ3: How do the distributions of men and women *retained to graduation* in CS differ?

2 Literature and Background

Since the mid-1980s, significantly fewer women than men have earned CS bachelor's degrees. After peaking at 37% in 1983, the percentage of women declined and plateaued below 20% throughout the 2000s and 2010s, only recently rising to about 22% in 2021 [30]. Main and Schimpf identified key themes across life and career stages that impact women in CS: high school (course-taking patterns and career interests), college major choice (stereotypes), college persistence (culture and self-efficacy), and post-college careers (work-life balance, culture, and mentoring) [50]. We next situate how our study extends the existing body of work.

Stereotypes and Career Perception: Gender disparities in computing begin well before college due to pre-college cultural context which discourages girls from taking CS courses in high school. Drawing on Valian's concept of gender schemas [78], research argues that the environment subtly steers girls away from CS (such as placing a computer in a boy's room) [51].

Stereotypes also play a critical role. Cheryan et al. [23] showed how cultural beliefs shape girls' and women's career interests in CS. By third grade, children already associate computing with males [53], and by high school, girls are less likely than boys to take CS courses [27, 42] and often view CS as uninteresting or misaligned with their goals. Carter [21] found that the top reasons for avoiding CS were a disinterest in sitting in front of the computer all day and a preference for other fields. Sax et al. [73] found that women valued social impact over theoretical contributions, reducing their likelihood of pursuing computing careers.

High school is a critical period for shaping students' decisions to pursue CS. Girls are less likely to take CS and other STEM preparatory courses, leaving them with limited exposure and understanding of the field upon entering college [20, 50]. A national study by Google found that high school experiences and exposure were more influential than college-level factors in women's decisions to major in and pursue careers in CS [35]. Pre-college experience is also linked to success in college CS courses [5, 17]. However, a follow-up study revealed a disconnect: students and parents viewed CS as highly important, while high school administrators placed less emphasis on it [49], limiting CS course offerings in high schools.

Self-efficacy, Sense of Belonging, and Sexism: Self-efficacy [7] and sense of belonging in CS have been extensively studied [25, 44, 54, 58, 60, 66]. Beyer et al. [13, 14] found that women, including those studying CS, reported lower confidence in computing than men, even those not pursuing CS. Using an expectancy-value framework [81], Beyer later showed that women preferred careers aimed to help others and society [12]. The framework of goal congruency highlights that students' sense of belonging increases when their personal goals align with their perceptions of a field's values [45]. Numerous studies have since confirmed that women exhibit lower computing self-efficacy than men [16, 22, 38, 62]. Lishinski et al. [47, 48] further linked self-efficacy to performance and retention, finding that women's self-efficacy was more affected by course-level experiences, making them more vulnerable to negative academic environments.

Research also shows that women in CS report a lower sense of belonging than men [43, 55–57, 72]. A Google/Gallup survey found parents were more likely to encourage CS for sons than daughters [49], and societal perceptions often portray CS as incompatible with traditionally "feminine" traits [28].

The Impact of College Admissions: The transition from high school to college is a pivotal point in students' educational trajectories, and college admissions policies can significantly influence the demographic makeup of CS programs. Despite this, the topic remains underexplored. Alexander et al. [2] examined the link between admissions policies and college outcomes, though not with a gender focus. Patitsas et al. [64] advocate for admissions reform to enhance diversity, while Nguyen and Lewis [60] and Smith et al. [74] find that competitive enrollment policies can deter women's participation. A 2023 ITiCSE working group studied CS admissions across four countries [6], highlighting gendered statistics. This study extends previous research by exploring the impact of admissions processes on gender diversity within CS.

Retention in CS at the College Level: Women are retained in CS at lower rates than men at all levels, including college [18, 24]. The 2017 "Generation CS" report shows a declining percentage of women from lower- to upper-division CS courses, indicating higher attrition among women [19]. The 2023 Taulbee survey reports a similar, though slightly less pronounced, trend [84]. Numerous studies have explored factors linked to CS retention [63]. Key predictors include self-assessed understanding, identity and belonging, math background, early course grades, and prior CS experience [3, 5, 10, 11, 65, 71, 77, 82]. Students who enter better prepared tend to succeed throughout programs. Social barriers, such as sexism, racism, and unwelcoming or irrelevant coursework, also contribute to women leaving CS [8, 9, 15, 40, 80]. A 2018 ACM report noted the lack of large, detailed datasets for multi-institutional retention analysis [75]. Broad datasets like BPS and IPEDS provide only high-level insights into student pathways. The Center for Inclusive Computing has recently compiled one of the most detailed multi-institutional datasets on early CS course demographics. Their studies now track factors influencing retention between early CS courses [33, 46, 59]. Our dataset follow specific student cohorts from application to graduation (or departure) at four universities, offering an unprecedented view into gendered path and retention patterns in CS.

3 Data and Methods

3.1 Data

We analyze data from four institutions, spanning Fall 2013 to 2023. Each institution provided student-level datasets², including admissions and retention records, which allow us to track students longitudinally from application through graduation or departure. The analysis of who applies and who is admitted to CS uses admissions data, while the analysis of retention in CS uses retention data.

Table 1: Institutional Statistics

	Inst. 1	Inst. 2	Inst. 3	Inst. 4
Type	Public/R1	Public/R1	Private/R2	Public/R2
Years of Data	2013-23	2013-23	2017-23	2013-23
Num Applied	645,241	-	143,938	1,111,714
Num Admitted	408,060	445,820	73,010	419,172

Table 1 summarizes institutional profiles, including type, total undergraduate enrollment, overall demographics, data coverage, and the number of applicants and admits across all majors. All institutions are located in the western United States. Institutions 1 and 2 are large R1 public universities, Institution 3 is a medium-sized private university with an undergraduate focus, and Institution 4 is a large R2 public university. Institution 2 reported only admitted students, so total applicant counts are not available.

Table 2 shows the number of all applicants and admitted students, and acceptance rates for the first and last years in our data. The data shown are for the first and last year in the data pool to indicate how the universities are changing in size, selectivity, and demographics over time. The table also lists average SAT scores [1], average high school Grade Point Average (HS GPA)³, percentage of women students, and percentage of freshman students⁴ for those who applied and who were admitted (in parenthesis)⁴ each institution in the last year of the data.⁵

Institution 1’s acceptance rate for the first year is 61.8%, climbing to 70.7% in the last year. It has the highest acceptance rate of the four institutions. Institution 3 has a 53.8% acceptance rate for the first year and a 48.0% for the last year, indicating some tightening of admissions over time. Institution 4 has an acceptance rate of 33.9% in the first year of the data, which rises to 48.9% by the last year. Due to data limitations (see Table 1), we are unable to estimate the exact admissions rate for Institution 2, but the institution’s website reports that it has acceptance rates of 26.8% for freshmen. High school GPAs range from about 3.75 to above 4.0 across all four institutions for those admitted.

The proportion of women students ranges from approximately 52% to 59%, reflecting a relatively even distribution across institutions. All four institutions enroll a substantial share of freshmen, with Institution 3 notably reporting nearly 88% freshmen.

²All data were provided under an exempt designation from the Institutional Review Board at each institution.

³GPA is a standardized measure of academic in the U.S., typically on a scale of 0.0 to 4.0 where 4.0 is excellent, 1.0 is poor, and 0.0 is failing. It is possible to exceed 4.0 with honors courses.

⁴In the US, students apply to attend university either directly after completing high school (freshmen) or after a small number of years of study at another college or university, typically a community college designed for this purpose (transfer).

⁵Note that Institution 2 only has the average scores for those admitted due to data limitations.

3.1.1 Admissions Data. The admissions data contain student-level records for all applicants for each year for each institution, including demographic details, academic preparation, and intended and admitted majors. However, not all institutions provided the same details. Table 3 shows which demographic and background variables each institution provided (shown as X).

Table 4 presents descriptive statistics for the variables used in our analyses, disaggregated by institution. We conducted separate analyses for freshmen and transfer applicants to account for differences in their characteristics. Due to space constraints, we present the results for the freshman population only. Results for transfer applicants are available upon request. Note also that the admissions data for Institutions 1, 3, and 4 are provided for the entire applicant pool, while data from Institution 2 are for admitted students only.

For categorical variables, values represent the proportion of individuals in each category (e.g., 11.6% of freshman applicants at Institution 1 are White). For continuous variables, we report the mean values along with standard deviations in parentheses (e.g., the average high school GPA for applicants at Institution 1 is 3.62, with a standard deviation of 0.509).

Race and gender, freshman status, high school GPA, and SAT/ACT scores appear across all four institutions, ensuring a shared core set of demographic and academic variables. Three of the four institutions provided three options for gender (“male/man”, “female/woman”, and “other”), but there were too few students included in the “other” category (less than .3% of students at each institution) to meaningfully analyze this category, and they are omitted from the table. Race was reported with varying levels of detail across institutions and was subsequently aggregated into the broader categories shown in Table 4, with an “Other” category used for students who did not fall into one of the primary classifications.

Income data are only included for Institutions 1 and 2, and first-generation college status (First Gen) is available only for Institutions 1 and 4. High school GPA showed considerable variation among applicants, with Institution 3 reporting a higher average GPA (4.02) compared with Institutions 1 and 4 (3.62 and 3.53, respectively). Institutions 1 and 4 were similar in the percentage of students who had taken AP Computer Science, AP Science (other than CS), AP Calculus, and any other AP taken. Institution 2 had higher AP percentages, but those reflect only the people who were admitted.

Due to a policy change in 2020-21, SAT scores were no longer required and therefore not available for any institution after 2020. When ACT scores were reported, they were converted to their SAT equivalents to maintain a consistent standardized testing metric. Accordingly, throughout this paper, we refer to all standardized test scores as SAT scores, with ACT results substituted by their SAT equivalents. Advanced Placement (AP) taken (whether a student took AP courses and which ones) is recorded at Institutions 1, 2, and 4, but not at Institution 3.

The CS applicants make up for 8.6% of the total applicants at Institution 1, 3.9% at Institution 3, and 5.4% at Institution 4. Admission rates to the CS major also varied among these institutions: 47% at Institution 1, 52% at Institution 3, and 41% at Institution 4.

Taken together, our admissions data show the breadth of institutional contexts with differences in size, governance, and focus. Overall, these four universities represent a somewhat diverse sample of types of universities in the US. Their selectivity spans a

Table 2: Institution Profiles: Applicants, Admits, Acceptance Rates in First and Last Years of Data; Average SAT and High School Grade Point Average (GPA), Percent Women and Freshmen for Applicants (Admits) in Last Year of Data

	Institution 1	Institution 2	Institution 3	Institution 4
Applicant (first year)	43,704	-	15,512	85,195
Admittant (first year)	27,011	32,545	8,350	28,900
Acceptance rate (first year)	61.8%	-	53.8%	33.9%
Applicant (last year)	74,895	-	24,330	111,023
Admittant (last year)	52,910	44,900	11,674	54,267
Acceptance rate (last year)	70.7%	-	48.0%	48.9%
SAT	1158.76 (1236.13)	(1397.53)	1243.74 (1317.32)	1048.87 (1150.23)
HS GPA	3.53 (3.75)	(4.33)	3.78 (4.01)	3.91 (4.14)
Women	51.9% (55%)	(52.4%)	58.5% (59%)	57.98% (59%)
Freshman	79.6% (79%)	(75.4%)	88.3% (88%)	65.06% (66%)

Table 3: Variables Included in the Admissions Data Sets for Each Institution

	Inst. 1	Inst. 2	Inst. 3	Inst. 4
Race	X	X	X	X
Gender	X	X	X	X
Freshman status	X	X	X	X
High School GPA	X	X	X	X
SAT Score	X	X	X	X
Income	X	X	-	-
First Gen	X	-	-	X
APs taken	X	X	-	X

mid-range for US Universities; selectivity categories that are not represented this set including highly selective private schools, and non-selective open-access schools. The gender balance at these universities is fairly typical of US universities, while the racial demographics are skewed toward Asian and Latinx and away from white and Black students due to the overall demographics where these universities are located.

3.1.2 Retention Data. Table 5 presents descriptive statistics on retention for freshmen-admitted CS majors. We limit our retention dataset to only students who started as CS majors at each institution; students who switched into CS are not included in our retention analysis, as our goal was to determine retention patterns for students who started college wanting to study CS. The retention data set was further restricted to students who took at least one university course and who were enrolled by 2018 so that they had an opportunity to be present for four years because we wanted to allow students enough time to graduate in a timely manner. Thus, students who enrolled after 2018 are not included in these analyzes.

The retention data contain high school preparation variables and demographic variables for all CS majors at each of the four institutions. Additionally, the retention data provides information on the courses taken each term (i.e., semester or quarter), grades received in those courses, change of major, the term GPA, and cumulative GPA. Institution 1 has retention data on all courses (both CS and non-CS courses) taken by CS students, while Institutions 2, 3, and 4 have only the CS courses taken by CS students. Institutions

Table 4: Descriptives of Variables by Institution for Admissions Data for Freshmen Applicants to all Majors per Institution (Inst. 2 Includes Admitted Students Only)

	Inst. 1.	Inst. 2	Inst. 3	Inst. 4
Women	54.8%	54.8%	59.1%	59.3%
White	11.6%	22.5%	37.5%	16.0%
Asian	39.6%	51.2%	12.7%	19.7%
Black	6.5%	3.1%	6.4%	4.5%
Latinx	38.7%	18.5%	23.0%	47.1%
Other	0.3%	0.4%	8.4%	5.2%
Race Unknown	3.3%	4.3%	12.0%	7.5%
First-Generation	53.4%	-	-	32.9%
Household Income (in 10,000s)	9.98 (-13.94)	16.5 (-17.36)	-	-
High School GPA	3.62 (-0.509)	4.36 (-0.285)	4.02 (-15.94)	3.53 (-0.559)
SAT Score (or equivalent)	1160.7 (-194.3)	1406.3 (-132.6)	1246.6 (-150.1)	1058.6 (-184.3)
AP Computer Science	0.9%	4.9%	-	0.5%
AP Calculus	3.5%	43.3%	-	3.0%
AP Science	4.9%	54.0%	-	2.5%
AP Other	8.0%	70.8%	-	6.7%
Applied to CS	8.6%	-	3.9%	5.4%
Admitted to CS	47.4%	-	51.8%	41.2%
Observations	513901	339101	127285	723226

1 and 2 are on a quarter schedule (three quarters per academic year), while Institutions 3 and 4 are on a semester schedule (two semesters per academic year).

3.2 Methods

3.2.1 RQ1: How do the distributions of men and women who apply to CS differ? We use the admissions data (Table 4) to address RQ1 by comparing the characteristics of applicants to the CS major with those of applicants to other majors, focusing on gender breakdown. To identify factors associated with applying to CS, we analyze the full applicant pool across all majors at each institution except Institution 2, which does not include a complete set of applicant data

Table 5: Descriptives of Variables By Institution For Retention Data (Freshman CS Majors Enrolled by 2018)

	Inst. 1	Inst. 2	Inst. 3	Inst. 4
Women	17.7%	20.5%	29.3%	16.2%
White	10.5%	16.1%	36.6%	11.6%
Asian	61.3%	69.1%	17.1%	45.8%
Blk/Ltn/Oth	19.9%	11.0%	29.3%	30.1%
Race unk.	8.3%	3.8%	17.1%	12.5%
First Gen	37.8%	—	—	26.9%
Family Income (in \$10k)	0.99 (0.98)	13.98 (11.93)	—	—
High School GPA	3.82 (0.30)	4.42 (0.21)	3.91 (0.37)	3.58 (0.37)
SAT (math)	684.4 (71.2)	747.0 (55.9)	—	—
SAT (rw)	648.8 (62.0)	701.9 (55.8)	—	—
SAT (total)	—	—	—	1196.4 (133.6)
AP CS	31.6%	11.4%	—	26.6%
AP Calculus	66.2%	90.0%	—	53.3%
AP Science	65.3%	88.3%	—	38.6%
AP Other	80.6%	93.8%	—	65.7%
Observations	1234	1941	123	1543

for all majors. To account for the SAT policy change implemented in 2020-21 (see Section 3.1.1), we separate our trend analysis to the periods before and after the policy shift.

Leveraging a decade of data, we begin by analyzing the raw application trends to observe how the percentage of women applying to the CS major has changed over time at each institution. Then we model the likelihood of applying to the CS major using logistic regression, to assess whether gender disparities can be explained or adjusted for by other factors. We treat an application to the CS major as a dichotomous (binary) outcome: either applying or not applying to CS. This model estimates the probability of applying to CS based on a comparable set of student-level covariates. The covariates included in our model are listed in Table 4 and include: gender, racial/ethnic identity, first-generation college status, family income, high school GPA, SAT score (for analysis applicable to years before 2020), and AP course preparation.

The model produces adjusted statistics regarding the applicant rates of students with particular gender, racial/ethnic, family education and income, and educational preparation characteristics. This analysis highlights factors that are significantly associated with a student’s likelihood of applying to the CS major, controlling for other factors relevant to the admissions process.

3.2.2 RQ2: How do the distributions of men and women admitted to CS differ? We also use the admissions dataset (Table 4) for Institutions 1, 3, and 4, to address Research Question 2 (RQ2) by comparing the characteristics of applicants who were admitted to the Computer Science (CS) major with those who were not, focusing on gender breakdown. Similar to RQ1, we separate our analysis for the periods before and after the policy shift in 2020-21.

We first consider the raw percentages of women admitted to CS over time to examine whether any raw trends are present. Then, we model the likelihood of applying to the CS major using logistic regression to assess whether gender disparities can be explained or adjusted for by other factors. We treat an application to the CS major as a dichotomous (binary) outcome: either applying or not applying to CS. This model estimates the probability of being admitted to CS based on a set of student-level covariates, using the same covariates as those used for modeling in RQ1. The model produces adjusted statistics regarding the admission rates of students with particular values for the covariates. It is used to identify factors significantly associated with the likelihood of being admitted to the CS major, while controlling for other covariates relevant to the admissions decision.

3.2.3 RQ3: How do the distributions of men and women retained to graduation in CS differ? We use the retention data set (Table 5) to analyze the students’ path through the CS program. At any given time point, a student can be in one of the four states: *Graduated CS* (taken to be the base outcome), *Graduated Non-CS*, *Left University*, and *Still Attending*. We analyze progress through these states by looking at retention at the end of four years.

This endpoint analysis is limited to all students who were admitted to CS and completed at least one term at their respective institutions, and whose gender was listed as “woman/female” or “man/male.” Dates for the first completed term and graduation events were directly determined from the retention data. Dates for which students left their respective universities without graduating were generally not available and were assumed to be the end of the last term enrolled, regardless of any formal withdrawal information. Complete records of enrollment in non-CS courses were provided only for Institution 1; for the other three institutions, enrollment information was provided for CS courses only, and it was assumed that non-graduating students left the university following their last reported CS course (corresponding to “Left University” students’ state). The 4-year endpoint analysis excluded students who started their first term after 2019, as they would not have enough time to reach their respective 4-year endpoints.

Endpoint outcomes were analyzed using multinomial logistic regression with the four above-mentioned outcomes and the set of covariates shown in Table 5. The regression finds the probability of a student being in one of the four outcome states by the end of four years.

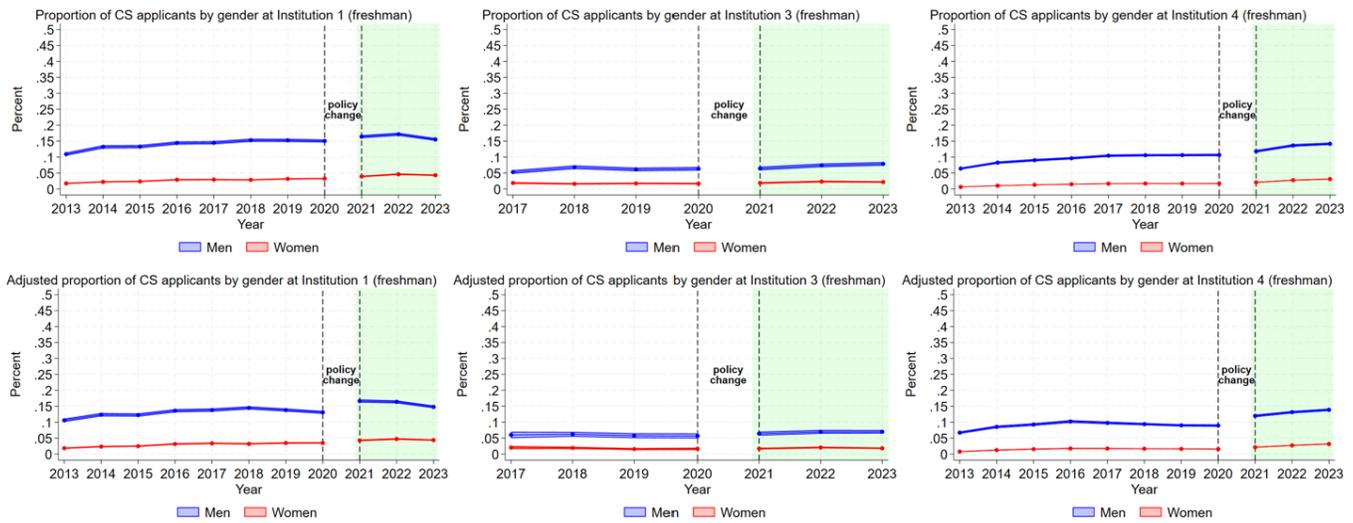
As the institutions provided slightly different variables (Table 3), subject to availability, covariates for each institution were gender, first-gen, race, whether a student took specific AP courses, and year of application (determined as the calendar year of the Fall term of the academic year for which application and admittance took place); and the continuous variables high school gpa, family income, SAT reading/writing scores, and SAT math scores. In our regression analyses, given that each institution is analyzed separately, we take advantage of all available variables for a particular institution.

4 Results

4.1 RQ1: How do the distributions of men and women who apply to CS differ?

Women apply to CS at much lower rates than men. In the last complete year of the data set (2023), for example, the percentage of

Figure 1: Gender Gaps in Freshman CS Applications Over Time (Institutions 1, 3, and 4): (a) Raw Applicant Percentages by Gender; (b) Adjusted Applicant Percentages by Gender



applicants to CS who were women was 24, 29, and 24 percent at Institutions 1, 3, and 4, respectively.

Figure 1.a) shows trends in the percentages of women and men freshman applicants by year over the observed period. The graphs show a line discontinuity from 2020 to 2021 to denote the policy change regarding the SAT score requirement. We see that gaps in the application rates between women and men persist over time and, in some cases (Institution 3), widen slightly, clearly showing that the CS major is not attracting women at the same rates as men.

Figure 1.b) shows the adjusted gender gaps in application rates to CS among freshmen over the observed period. To account for the policy shift, the models include student SAT scores for the pre-2020 data, while they exclude student SAT scores for the post-2021 data. Notably, the gender gap in CS applications persists even after controlling for a comprehensive set of covariates through a regression comparing CS applicants to those applying to other majors. This indicates that when comparing women and men with similar academic preparation and pre-college pathways, women remain less likely to apply to CS. Across the three institutions studied, there is no evidence of a significant reduction in the gender gap over the past decade. The adjusted trends closely mirror the raw data (almost identical). At Institution 1, the proportion of women applying to CS is consistently about 10% lower than that of men, with the gap widening to 20 % after 2021. At Institution 3, the gap remains steady at approximately 8%, while at Institution 4, the disparity increases after 2021, reaching to approximately 15%.

Table 6 presents the regression output for the adjusted application rates for freshmen. Due to space constraints, we limit all of our regression table outputs to only display the gender variable and the preparation variables. Full regression results are available upon request. The regression table presents average marginal effects from logistic regressions predicting the probability of applying to a CS major at each institution. Each institution's results are organized

Table 6: Regression Output Table For Students Who Applied As Freshmen to CS Versus Other Majors at All Institutions

	Institution 1		Institution 3		Institution 4	
	pre '21	post '21	pre '21	post '21	pre '21	post '21
Women	-0.10*** (0.00)	-0.11*** (0.00)	-0.042*** (0.00)	-0.049*** (0.00)	-0.076*** (0.00)	-0.10*** (0.00)
High School GPA	0.0024** (0.00)	0.031*** (0.00)	0.0028 (0.00)	0.022*** (0.00)	0.0030*** (0.00)	0.033*** (0.00)
SAT Score	0.00013*** (0.00)		0.000086*** (0.00)		0.000081*** (0.00)	
AP CS	0.22*** (0.01)	0.22*** (0.01)			0.20*** (0.01)	0.23*** (0.01)
AP Calculus	0.022*** (0.00)	0.051*** (0.01)			0.017*** (0.00)	0.023*** (0.01)
AP Science	-0.017*** (0.00)	-0.037*** (0.00)			-0.0017 (0.00)	-0.0084* (0.00)
AP Others	-0.043*** (0.00)	-0.064*** (0.00)			-0.016*** (0.00)	-0.035*** (0.00)
Observations	334048	164613	34142	54567	442723	221570
Standard errors in parentheses						
* p<0.10 ** p<0.05 *** p<0.01						

into two columns: pre-2021 and post-2021. Because each institution includes a somewhat different set of control variables, direct comparisons of coefficient magnitudes across institutions should be approached cautiously; nonetheless, broad patterns can still be compared, with the recognition that some results are slightly more robust than others.

At all three institutions, we see consistently lower percentages of women of similar qualifications applying to CS than men at the freshman level. Moreover, all three institutions experienced a

Figure 2: Gender Gaps in Freshman CS Admissions Over Time (Institutions 1, 3, and 4): (a) Raw Admission Percentages by Gender; (b) Adjusted Admission Percentages by Gender.

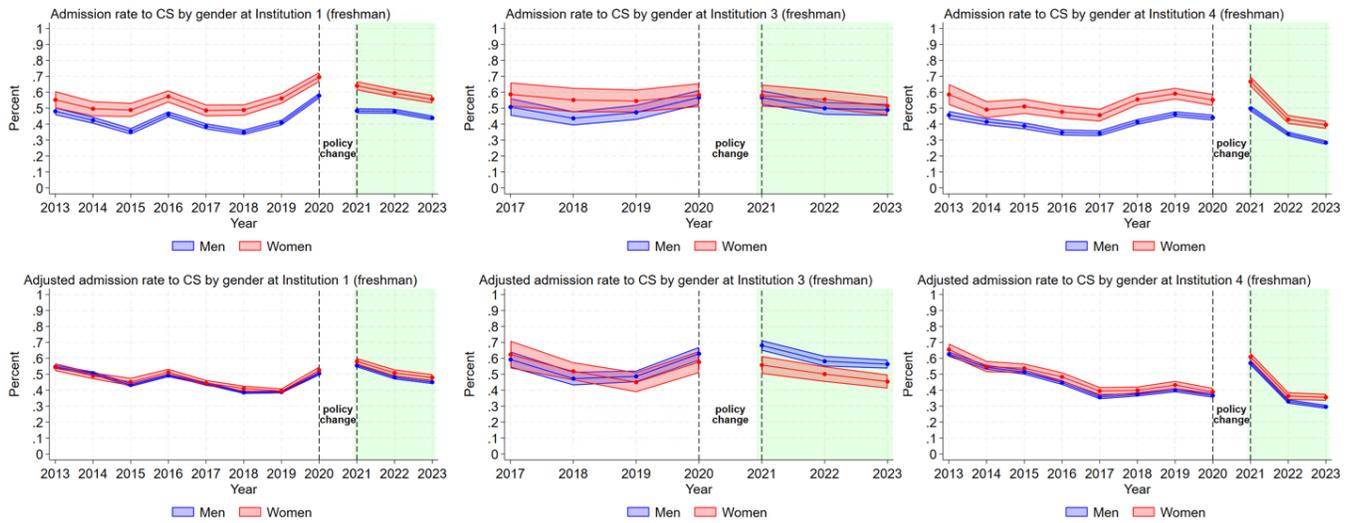


Table 7: Percentages of Students Admitted to the CS Major (Out Of The Total Number Of Students Who Applied) at Institutions 1, 3, and 4 for Freshman Students for the Year 2023

	Women		Men	
	Apply[#]	Admit[%]	Apply[#]	Admit[%]
Inst. 1	1387	55.70%	4376	43.90%
Inst. 3	286	51.40%	707	48.90%
Inst. 4	1470	39.60%	4619	28.40%

widening of this gap after 2021 (e.g., increasing from -0.076 pre-2021 to -0.10 post-2021 at Institution 4), with all associations highly significant ($p < 0.01$). Pre-college preparation is also associated with application rates to CS. Higher GPAs and higher SAT scores (before 2020) are positively associated with application to CS for all institutions, and the coefficient on GPA increases, as would be expected in the post '21 period when SAT scores are not considered in the admission process, signifying a stronger association of GPA and admission. All advanced placement (AP) exams are positively and significantly associated with application rates to CS, except AP Science for Institution 4.

The results indicate that women are significantly less likely than men to apply to computer science (CS) compared to other majors, even among those with similar academic preparation. The inclusion of covariates did not close gaps, suggesting that strong gender-based differences in interest or preferences for CS emerge early in the pathway and are evident at the application stage.

4.2 RQ2: How do the distributions of men and women admitted to CS differ?

The second stage of the CS pathway is admittance. Table 7 provides the percentages of the number of students who were admitted to CS

out of the number of women (or men, respectively) who applied to CS for the last year in the data set. The percentages in 2023 reveal that freshmen women are being admitted at higher rates than men at all three institutions, and the difference is significant in all three Institutions.

Figure 2.a) shows the trends over time across all years of data available for each institution as the percentages of freshmen admits to CS (out of those who applied to CS) for each gender. Over time, we see women consistently admitted to CS at higher rates than their male counterparts at Institutions 1 and 4. Institution 3 rates show a similar but less pronounced pattern. This suggests that the admissions stage partially mitigates the gender imbalance observed at the application stage in favor of men.

When controlling for our set of covariates, however, our gaps close in all three institutions, and men and women are admitted at similar rates for both freshmen groups. Figure 2.b) shows the adjusted admission rates to CS for women and men over time. Institutions 1 and 3 show almost identical admittance rates for men and women. This suggests that when accounting for pre-college preparation and other demographic characteristics, men perform as well as women in admittance to CS. This result implies that when all else is equal in preparation, women are being admitted at the same rates as men and are, thus, neither gender receives preferential treatment at these institutions. However, at Institution 3, a modest gender gap favoring men appears at the admission stage after the policy change removing the SAT requirement.

Table 8 gives the regression results for admittance, examining the effects of specific covariates. In Institutions 1 and 4, we see the gender gap reappearing in the post-2020 years. The values for women's admittance after 2021 are higher than those before 2021, and the difference is statistically significant at $p < 0.01$. This suggests a possible change in pattern after the policy change (exclusion of SAT scores). High school GPA, SAT, and APs are all significantly

Table 8: Regression Output Table for Admittance for Freshmen at All Institutions

	Inst. 1		Inst. 3		Inst. 4	
	pre '21	post '21	pre '21	post '21	pre '21	post '21
Women	0.011*** (0.00)	0.027*** (0.01)	-0.0014 (0.02)	-0.10*** (0.02)	0.028*** (0.01)	0.046*** (0.01)
High School GPA	0.40*** (0.00)	0.58*** (0.01)	0.47*** (0.02)	0.80*** (0.01)	0.30*** (0.01)	0.36*** (0.01)
SAT Score	0.00094*** (0.00)		0.0015*** (0.00)		0.0011*** (0.00)	
AP CS	-0.040* (0.02)	-0.022 (0.05)			0.11*** (0.02)	0.092*** (0.03)
AP Calculus	0.13*** (0.02)	0.17*** (0.04)			0.095*** (0.02)	0.20*** (0.04)
AP Science		0.100** (0.04)			0.012 (0.02)	0.014 (0.03)
AP Others	0.16*** (0.02)	0.19*** (0.03)			0.19*** (0.01)	0.26*** (0.03)
Observations	26169	16280	1221	2084	21377	15415

Standard errors in parentheses
* p<0.10 ** p<0.05 *** p<0.01

associated with admittance to CS at Institution 1. At Institution 3, HS GPA and SAT are also significant, with the higher values compared to Institution 1, of both being positively associated with admittance. At Institution 4, admittance is associated with High school GPA, SAT, and several of the AP variables.

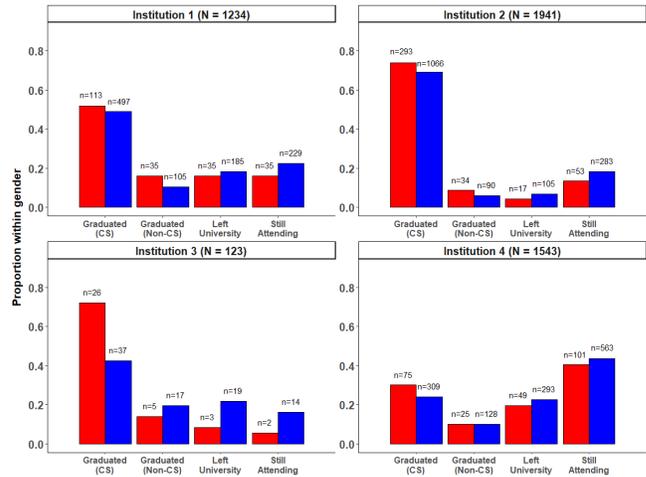
Overall, the results suggest that the admission stage mitigates some of the gender gaps observed at the application stage. Although women are admitted at similar rates, these rates are relative to the smaller number of women who apply to CS. Consequently, the broader pathway imbalance stemming from application gaps remains unresolved.

4.3 RQ3: How do the distributions of men and women retained to graduation in CS differ?

Our retention analysis includes all four institutions. We examine students' four-year outcomes and analyze gender differences in these endpoints. Figure 3 illustrates the relative percentage of women and men in each of four possible end states: (1) Graduated in CS, (2) Graduated in non-CS, (3) Left the University, or (4) Still Attending after four years. Red bars represent women and blue bars represent men. N denotes the total number of students in the four-year dataset for each institution, and n indicates the number of students at each endpoint. Proportions are calculated within gender across the four endpoints. 52% of women who started in CS as freshmen at Inst. 1 graduated in CS within four years. This rate is slightly higher than the rate for men (49%) at the same institution. About 16% of women switch out of CS at some point and graduate in a non-CS major within four years, exceeding the rate for men graduating in a non-CS major (10%). Women leave the university at lower rates than men (16% versus 18%), and men are still attending at the end of four years at higher rates than women (18 versus 13%). This same

relative pattern exists at Institutions 2 and 4. At Institution 3, the smaller private institution, women graduate in CS within four years at a much higher relative rate than men (women at 72% vs. men at 43%).

Figure 3: Four-Year Endpoint Outcomes for Freshmen Entering 2013–2019, by Institution: Women (Red) vs. Men (Blue).



To further investigate retention outcomes for freshman entrants, we use four-outcome multinomial logistic regression to examine whether gender is significantly related to ending up in each of the four specific states once we control for a set of covariates. Table 9 shows the regression results for the gender, first-generation status, and high school preparation coefficients for the four-year cut-off. We report coefficients for two states: the Graduating in Non-CS (GN-CS) and the Left University (LV), which are to be understood in comparison to the omitted reference category of Graduating in CS.⁶

The regression analysis for freshman entrants reveals that while holding constant a set of other characteristics, women have a higher likelihood than men of graduating in non-CS versus CS at Institution 1 and a lower likelihood than men of leaving their institution versus graduating in CS at Institutions 2 and 3. There are no apparent gender differences at Institution 4 (that are statistically significant). One caveat in interpreting these regression results is that cross-institution comparisons are not appropriate, as each model includes a different set of covariates reflecting the available data at each institution (given that each institution provided a different set of available data).

We see that high school preparation is also significantly associated with outcomes. The higher a student's high school GPA, the less likely they are to leave the institution (versus graduating in CS) at Institution 1, to graduate in non-CS at Institution 2, or do either at Institution 4. In addition, those who take AP CS in high school are less likely to graduate in non-CS or leave the university than graduate in CS in both Institutions 1 and 4. Overall, the regression

⁶For the sake of space and brevity, we have not shown the coefficients for the "Still Attending" state.

Table 9: Regression Output For Four-Year Endpoints For Freshmen Entering Between 2013 and 2019

VARIABLES	Inst. 1		Inst. 2		Inst. 3		Inst. 4	
	GN-CS	LV	GN-CS	LV	GN-CS	LV	GN-CS	LV
Women	0.495** (0.247)	-0.018 (0.225)	0.174 (0.225)	-0.641** (0.278)	-0.718 (0.596)	-1.467** (0.692)	-0.359 (0.268)	-0.314 (0.224)
First Gen	0.641*** (0.233)	-0.014 (0.198)	—	—	—	—	0.006 (0.237)	0.153 (0.195)
HS GPA	0.072 (0.409)	-0.888*** (0.313)	-1.415*** (0.484)	-0.470 (0.481)	0.426 (0.734)	-0.630 (0.708)	-0.904*** (0.297)	-2.260*** (0.243)
SAT (rw)	0.497 (1.997)	1.697 (1.639)	-10.320*** (2.096)	-9.391*** (2.218)	—	—	—	—
SAT (math)	-4.547** (1.820)	-0.310 (1.538)	-1.664 (2.103)	-0.284 (2.165)	—	—	—	—
SAT (total)	—	—	—	—	—	—	-3.142*** (0.903)	-1.447** (0.732)
AP CS	-1.153*** (0.295)	-0.493** (0.204)	0.126 (0.330)	-0.321 (0.343)	—	—	-0.814*** (0.244)	-0.880*** (0.200)
AP Calculus	-0.407* (0.226)	-0.171 (0.193)	-1.018*** (0.295)	-0.949*** (0.308)	—	—	-0.614*** (0.236)	-0.652*** (0.198)
AP Science	-0.112 (0.234)	-0.518*** (0.195)	0.330 (0.297)	0.259 (0.310)	—	—	-0.726*** (0.231)	-0.472** (0.192)
AP Other	0.298 (0.287)	-0.265 (0.229)	0.638 (0.462)	-0.030 (0.407)	—	—	0.892*** (0.265)	-0.070 (0.204)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

analysis shows significant differences in retention by gender and academic preparation across all institutions.

5 Discussion

Our comprehensive analyses of the pathways in CS indicates that gender gaps are present in the application stage, narrowed or closed in the admittance stage, and mostly do not reappear in the retention stage, though what happens to men and women who leave the CS major differs. Our results reinforce some previous findings while providing additional nuances to our understanding. Our results also provide missing information about CS retention by gender at the university level. The main themes that our results support are:

Pre-college experience is not enough. We found large gender gaps in the percentages of applicants to CS programs at all three institutions. These gaps did not disappear when we controlling for prior experience and academic outcomes including GPA and AP course completion, or background factors such as income level. In other words, given two students, one man and one woman, with the same formal exposure to CS and similar life context, the man is more likely to apply preferentially to a college CS program (versus another program) than the woman.

This result suggests that early exposure to CS is insufficient on its own. Barriers reported by previous research, including cultural stereotypes and negative perceptions of the field [52, 53], as well as sexism and racism [67, 68] are not sufficiently overcome by students' formal CS experience or academic success. Earlier interventions that actively counter negative gender-related stereotypes about computing are necessary. Prior research has also found that support

is critical in helping girls and women decide to pursue or stay in computing [16, 26, 29, 34, 36, 37, 69, 70]. Our results suggest that a critical time for this support is when students are deciding what they want to apply to study in college. Yet, while pre-college CS courses do not close the gender gap in application rates, our results show that they do increase *all* students' likelihood of applying preferentially to a college CS program; thus, increasing the number of women who pursue these opportunities will help expand the overall pathway for women in the field. Addressing the gender imbalance in pre-college CS courses *will* help address the gender imbalance at the college level.

The gender gap in interest in a college CS major is widening. With the rise in popularity of CS over the last 10 years, there is a concern that as CS becomes more competitive, it will also become less diverse. Some work has shown that competitive admissions processes disproportionately turn women away from CS [60, 74], and our results somewhat support this idea as well. We found that the increased gender gap in CS applicants is more recent, starting in 2021. Because of this timing, this increased gap might also be associated with the COVID-19 pandemic.

Women CS college applicants are, on average, stronger candidates than men. Our results show that women CS applicants are admitted to CS programs at higher rates than men, but that this difference is drastically reduced when other factors, including academic factors, are considered. Our results indicate, not surprisingly, that high school GPA and completion of AP courses are associated with admission. To further examine the relationship between gender and preparation, we computed the average GPA

at all institutions and for freshmen and transfers at the different points in the trajectory. We found that women applicants' GPAs were on average higher than men applicants' GPAs at all points in the trajectory and at all the institutions. Although the gender gaps did not fully disappear in admittance when our covariates were included, some unaccounted for differences might be due to other factors that were not measurable or included in our data set. For example, we did not consider admissions essay scores, which is, in some institutions, an important part of the admissions process. Our analysis supports the idea that differences in acceptance rate by gender are due not to preference for women applicants, but rather due to academic factors where women applicants are performing better.

Women generally graduate equally well (or better than) men from college CS programs. Our results show that women are retained in college CS at similar relative rates as men. At all four institutions, the proportion of freshman-admitted women in CS who graduate in CS in four years is higher than the proportion of freshman-admitted men graduating in CS in four years.

The results indicate that retention of women overall in college CS programs might not be the problem it is thought to be and bolsters the results reported by Stephenson et al. in 2018 [75]. Their analysis tracked the percentage of women at each year of the college major and found that the percentage of women across the years held steady or increased. However, they acknowledged that their study was not a true retention study because they could not use a cohort-based approach. Our study uses the cohort-based approach, tracking the same students through four undergraduate CS programs for eight full cohorts of students (2012-2019). This approach provides further support for the idea that once women are in a CS program, they are retained at similar levels to men.

Women and men have different destinations when they change out of CS in college. We found that women change out of the CS major and graduate in a non-CS major at a higher rate than men. Among students who change out of the CS program, women are more likely to graduate in a different program at the university, while men are more likely to leave the university entirely.

This result implies that the strategies for retaining women and men in CS might be different. For women, strategies that highlight the social impact of the field and combat negative cultural and group-work experiences (e.g. relevant and culturally competent curricula, cultural interventions, same-gender pair or groupwork, Women in Computing groups [4, 23, 39, 80, 83]) may have the biggest impact, while for men the focus could be on supporting them as university students overall.

Indeed, research shows that the culture and curriculum of a CS department can strongly shape women's engagement [4, 32, 41, 51]. This is particularly evident in the comprehensive interventions at Harvey Mudd College (HMC) and Carnegie Mellon University (CMU). Addressing culture at the college level could not only help with retention, but could also encourage more women to apply in the first place.

5.1 Limitations

Our study has some limitations. First, we studied a small number of institutions that are all geographically located in the same region

of the US. Therefore, while the institutions vary in size, focus, public vs. private, and selectivity, these results may not apply to all institutions.

Second, the variables we were able to include based on the data we obtained do not explain the entirety of a student's circumstances, and there could be additional underlying factors that explain some of the differences we observed. In addition, due to different specifications at each institution, cross-institutional comparisons are limited.

Additionally, programs that directly support women can influence any stage of the pathway. However, our institutions lack such programs, and public universities in California are prohibited from exclusivity based on race or gender. Student clubs supporting women and underrepresented populations do exist, but their impact is addressed qualitatively and is beyond the scope of this paper. ?

Lastly, this paper focuses on women as a single group. This approach ignores the fact that women from different races, socioeconomic backgrounds, and family education backgrounds may have different paths, experiences, and outcomes. We have already begun to carry out intersectional research that combines race and gender, but due to the scope of this paper, we did not have room to explore it here. It will be a subject of future work.

6 Conclusion

We used a data-intensive approach to understand application, admission, and retention patterns in CS at four different institutions with different characteristics and student bodies. Our work provides new insights on how to increase the number of women in the CS pathways. Our findings highlight the importance of efforts to support women and change their perception of CS early—before they apply for college. Women are strong candidates for admission into the CS major and those that do apply are admitted at similar rates to men. Our work also suggests approaches for student retention in the CS major. Future work will focus on further understanding more nuanced parts of the undergraduate CS pathway to graduation.

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