Can Computing Be Diversified on “Principles” Alone? Exploring the Role of AP Computer Science Courses in Students’ Major and Career Intentions

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The Advanced Placement Computer Science Principles (APCSP) course was introduced in 2016 to address long-standing gender and racial/ethnic disparities in the United States among students taking Advanced Placement Computer Science (APCS) in high school, as well as among those who pursued computing majors in college. Although APCSP has drawn a more diverse population of course takers than the traditional Advanced Placement Computer Science A (APCSA) course, questions remain about whether the new course portends students’ longer-term interest in computing and technology. This study used data from more than 120,000 first-year college students in the United States to understand the relationship between taking APCS, APCSP, or both APCS courses and students’ aspirations to major in computing or to pursue a computing or technology career. Our results indicated that taking APCS or taking both APCS courses positively predicted students’ major or career aspirations in computing and technology, but that taking only APCSP did not predict long-term computing interest (although positive associations were identified for women). The findings identify a possible tension in the function of APCSP, as it appears to broaden access to computing knowledge, but may not necessarily encourage longer-term computing aspirations for all groups of underrepresented students.

CCS Concepts: • **Social and professional topics** → **Professional topics; Computing education; Computing education programs; Computer science education;**

Additional Key Words and Phrases: AP Computer Science A course/exam, AP Computer Science Principles course/exam, gender and race/ethnicity

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1 INTRODUCTION

Computer science (CS) holds immense power and influence in our global society and economy, and yet from its origins has been and remains an elite and exclusionary field. Indeed, despite recent concerted efforts in the United States to broaden participation in the field, the demographics of the innovators and creators of technology still do not reflect the racial, cultural, and gender diversity of our society [28]. Exemplifying this imbalance, women represent 57% of the total U.S. workforce but constitute only 26% of the computing workforce [45], and although Black and Hispanic workers constitute 11% and 16% of the total workforce, respectively, each group represents only 7% of the computing workforce [22].

Disparities in computing participation begin early in school settings, as the literacies and experiences shown to motivate youth to enroll in introductory CS courses are often acquired through out-of-school programs predominantly accessed by students from affluent families [3, 29]. For people from historically minoritized groups to benefit from participating in and shaping the computing field, and for the computing field to reflect and benefit from the rich diversity of the larger society, a broader profile of youth must consider studying CS in higher education, and computing’s distinction as an elite form of knowledge must be dismantled at the elementary and secondary school levels [1, 39]. A key focus of such efforts to **broaden participation in computing (BPC)** has been to expand CS education opportunities in the United States. In the past 10 years, a series of policy reforms and industry-backed investments have steadily increased access to CS learning opportunities in working-class neighborhoods in the United States through after-school programs [38], summer coding camps [40], and library makerspaces [9], and through the introduction of computing courses like Exploring Computer Science in high schools across the country [24, 44].

In this article, we examine another BPC initiative, the relatively new **Advanced Placement (AP)** course that launched in 2016: **Advanced Placement Computer Science Principles (APCSP)**. APCSP was designed specifically to increase interest in CS among a more diverse population of high school students and to expand the number of students prepared to meet the labor demands of the exponentially growing computing workforce [18, 68]. We compare three groups of students—those who took the new APCSP course, those who took the legacy **Advanced Placement Computer Science A (APCSA)** course, and students who took *both* **Advanced Placement Computer Science (APCS)** courses—to examine the extent to which these courses portend undergraduate students’ intentions to major in or pursue careers in computing.

2 REVIEW OF THE LITERATURE

2.1 The School-Career Computing “Pipeline”

The pipeline metaphor is frequently used to explain demographic disparities in **science, technology, engineering, and math (STEM)** education and the workforce, as it demonstrates how an essential series of experiences and knowledge starting in childhood are necessary for entry into certain elite professions [43]. The pipeline analogy is particularly pervasive in CS education research [59], given the tendency to view computing education as the key to computing majors and jobs [3, 29]. Thus, based on the pipeline metaphor, persistent demographic disparities in the field

can be attributed in part to the fact that affluent white male students simply take more preparatory CS courses progressively through high school and beyond [30, 46].

However, the computing career pipeline metaphor has been critiqued for ignoring the broader systemic forces that perpetually limit opportunities for students to access the coursework and social capital necessary to enter and remain in the computing pipeline [44, 59, 66]. Further, the metaphor fails to explain why the gender and racial/ethnic disparities prevalent in computing majors and careers in the United States, Canada, and Western Europe are not observed elsewhere in the world [32]. Accordingly, programmatic efforts to address diversity in STEM careers using pipeline metaphors have been criticized for forwarding a westernized neoliberal paradigm of education and failing to acknowledge the problematic and undemocratic nature of science itself [42]. Indeed, when it is assumed that there is a single pathway to computing majors and jobs, touchstones like APCS courses can act as gatekeepers that exclude individuals from entering the pipeline, disproportionately affecting students impacted by a nexus of systemic oppressions like racism, sexism, and classism, who are least likely to have access to such courses [66].

A long-standing offering in the computing pipeline is APCSA, a high school elective first offered in 1984. With a focus on Java programming, APCSA was designed to be comparable to a college-level introductory class for CS majors and is considered a valuable gateway course for high school students in the United States; it is closely associated with career readiness and interest in pursuing employment in a computing field [3, 29]. A longitudinal study revealed that 18% of APCSA course-takers eventually majored in a computing-related domain in college, a rate eight times higher than AP students of other courses [41]. In addition, grades earned in AP classes can augment a course-taker’s high school **grade point average (GPA)**, and a passing score on the end-of-course AP exam is often exchanged for undergraduate credit and higher placement in the CS course sequence in college [15].

Despite the role that early CS course-taking plays in shaping subsequent pursuit of CS, scholars have found that computing courses are taught at only about half of the high schools across the United States and that, among the classes that are offered, nearly half do not actually introduce students to programming concepts [5]. In fact, although AP courses are available to students across the globe through in-person schools and online programs, APCSA, like all AP courses, is offered more consistently at high schools in affluent neighborhoods in the United States [5, 58, 63], where educators explicitly steer many more students toward computing opportunities [23, 39]. In part because of this inequitable access to courses across schools, 78% of APCSA exam-takers identify as white or Asian [68]. To summarize, although students without access to AP classes are already disadvantaged when applying to college [63], taking and passing APCSA gives other students a competitive edge and accelerates individuals toward related college majors and careers in CS in the United States and at the more than 400 institutions outside the United States that use AP courses in their admissions and course-placement procedures [14].

2.2 APCSP to Broaden Participation in Computing

In the aforementioned historic movement of sweeping national BPC efforts in the United States—and with significant support from the National Science Foundation and unprecedented influence from the technology industry and industry-backed non-profit partners—the College Board, which administers the AP program, designed a new introductory CS course. APCSP was conceived to address the long-standing racial, gender, and socioeconomic disparities represented in APCSA, in higher education, and in computing careers in the United States [3]. College Board president and CEO David Coleman articulated that the purpose of APCSP was to “cultivate an interest in CS among students of all backgrounds” and to prepare course-takers for “the computing jobs that will

help power future economic growth” [25]. In other words, he explicated before the course launched that two key goals of APCSP were to diversify the group of students who studied computing in high school (expand access to the pipeline) and increase the number of trained and qualified people who will eventually work in computing (broaden the pipeline).

To “motivate and educate a substantially larger number of students to fulfill the demands of the market while reaching a broader, more diverse segment of the population” [2], APCSP course content emphasizes the big intellectual and fundamental ideas of computing. The focus on foundational concepts in computing such as creativity, abstraction, data and information, algorithms, programming, the Internet, and the global impact of computing—rather than APCSA’s narrower focus on programming—was designed in part to better attract and retain students from groups that are underrepresented in computing, including girls, people of color, and persons with disabilities [18]. Further, unlike APCSA, which assesses student learning with a summative final AP exam, a distinct aspect of the APCSP assessment is the inclusion of an applied performance task, centering choice and creativity in students’ computational work, which is created during classroom instructional time and ultimately accounts for 40% of students’ final AP score.

2.2.1 The Launch of APCSP. In fall 2016, APCSP had the largest launch of any AP course in the College Board’s history [15]. In its inaugural year, 43,780 students from 2,500 schools took the APCSP exam [16]; by 2018, this figure had more than doubled to 94,360. Headlines from organizations that promoted diversity initiatives in computing touted victory, stating: “Girls and minorities break records in computer science as fastest-growing groups . . . thanks to the record-breaking launch of the new Computer Science Principles” [12]. To be sure, recent data suggests that APCSP attracts a far more diverse group of students in terms of gender and race/ethnicity than does the traditional APCSA course [55, 68], although participation among girls and Black and Hispanic students still does not mirror the diversity of the nation’s high school student body.

Although there is evidence that APCSP contributes to both expanding and diversifying the pool of high school students learning college-level CS, there is more to explore about what role APCSP plays in ultimately diversifying computing spaces in higher education and the workforce. Evidence from the College Board [68] suggests that the introduction of APCSP is correlated with a growing number of students majoring in CS in college, revealing that students who take APCSP are more likely to major in CS in college than similar students who graduated high school just prior to the introduction of APCSP (16.9% in 2019 vs. 5.2% in 2016). Their analysis matched students graduating high school in 2019 with those graduating in 2016 in terms of gender, race/ethnicity, parental education, high school GPA, and SAT; however, it did not account for additional variables that may correlate with enrollment in APCS courses or otherwise predict major choice, which is a goal of the present study.

3 OBJECTIVES

This empirical inquiry builds on prior studies of college students who had participated in one or both APCS courses [26, 57, 68] to examine associations between taking APCSA, APCSP, or both APCS courses and students’ aspirations to pursue majors or careers in computing. The study includes a set of control variables similar to that used in the College Board [68] study (e.g., gender, race/ethnicity, parental education, high school GPA, and standardized test scores), in addition to a wide range of other covariates associated with major and career decision-making. Specifically, using 2017 data from **The Freshman Survey (TFS)**, a nationwide survey of first-year college students administered the year following the formal launch of APCSP, we examined the following research questions:

- (1) How does taking APCSA, APCSP, or both APCS courses correspond with students’ intent to major in a computing field or aspire to a career in computing, and how does this vary by students’ gender or race/ethnicity?
- (2) Controlling for proxies for academic achievement (e.g., high school GPA, SAT/ACT scores), to what extent does APCS course-taking predict students’ intent to major in a computing field or aspire to a career in computing?
 - (a) Are there differences in the predictive power of taking only APCSP, only APCSA, or both APCS courses?
 - (b) Does the predictive power of taking each course differ by students’ gender or race/ethnicity?

4 METHODS

4.1 Data Source and Sample

Data for this study were provided by UCLA’s **Higher Education Research Institute (HERI)**. Each year, HERI administers TFS to first-year college students attending institutions that participate in the Cooperative Institutional Research Program. Administered annually since 1966, this comprehensive survey asks respondents about their demographic characteristics, values and beliefs, academic and social involvement during their last year of high school, and their expectations and goals for their college experience and career. This study relied on data from the 2017 TFS, as the APCSP course officially launched in fall 2016 (with a more limited set of schools piloting the course and exam in the 2 years prior) [19]. Thus, these TFS respondents from 168 four-year colleges and universities [64]¹ are the first class of students who would have had the opportunity to take the fully approved and more widely offered APCSP course. Among the more than 129,000 respondents in our sample are 6,098 students who took only APCSA, 1,851 who took only APCSP, and 896 who took both APCS courses. Demographically, 58.6% of respondents from the full TFS sample indicated they were women, and the racial/ethnic distribution of the sample was as follows: 0.2% were American Indian, 14.5% were Asian or Asian American, 8.7% were Black or African American, 8.7% were Hispanic or Latinx, 55.3% were white, 11.9% indicated two or more races/ethnicities, and 0.8% were some other race/ethnicity.

4.2 Social Cognitive Career Theory

We employed **social cognitive career theory (SCCT)** [34] as a framework to guide our investigation of the relationships between APCS course-taking and intentions to pursue a computing major or career. Based on Bandura’s social cognitive theory [4], SCCT models how an individual’s personal characteristics (e.g., race/ethnicity, gender, academic achievement) and their learning experiences might interact with their self-efficacy beliefs, expectations, interests, and goals, to ultimately shape their academic and career aspirations [34–36]. The model accounts for a wide variety of student identities and conditions that impact students’ career development and has been found to be helpful for framing educational and career development in STEM fields broadly [11, 62, 67] and in specific fields like computing [33, 57] and engineering [27, 31]. Additionally, scholars have used SCCT to explore how secondary and postsecondary schools might increase the participation of students historically marginalized in STEM education [21, 47, 53, 65]. Our study builds on this prior research by using SCCT to investigate the potential of APCS course-taking in increasing the racial/ethnic and gender diversity in computing and technology, which is a stated goal of the APCSP course [19]. See Figure 1 for our adaptation of the model.

¹Detailed demographic characteristics of APCS course-takers among the 2017 TFS respondents can be found in our earlier work [57].

Fig. 1. SCCT model. Adapted from Lent et al. [34].

We applied SCCT to control for a wide variety of experiences, beliefs, and interests that inform two different *choice goals*, defined as the “intentions, plans, or aspirations to engage in a particular career direction” [34] among undergraduate students: (1) their intent to major in computing and (2) their aspirations for a career in computing/technology. However, for the purposes of this study, we were most interested in the role of particular *learning experiences*: having taken APCS, APCSP, or both APCS courses. The SCCT framework suggests that *person inputs* (e.g., race/ethnicity, gender) and *background contextual affordances* (e.g., family income, parent education) often dictate students’ access to and perceptions of learning experiences, and it is such learning experiences (like APCS courses) that inform individuals’ *self-efficacy*, or beliefs about how well one will execute tasks or be successful in a specific domain [34]. Thus, the model suggests that the greater an individual’s self-efficacy in a task like computer programming, for example, the more likely they will be to have more positive *outcome expectations* of majoring or working in a computing field successfully. Self-efficacy and outcome expectations also influence students’ *interests* or enjoyment in participating in activities, especially those related to the choice goal in question [34]. Consequently, these interests inform students’ *choice goals*. Finally, the framework accounts for the fact that students develop interests, goals, and aspirations about their careers amidst particular *contextual influences*.

4.3 Measures

Our logistic regression analyses (described in the following) relied on two dependent variables: (1) students’ intent to major in computing and (2) students’ intent to work in a computing or technology profession. The computing major variable was created by aggregating 90 options for academic major into a dichotomous measure for intended computing major. Students were considered computing majors if they indicated their probable major was “computer science,” “computer/management information systems,” or “other math/computer science.” If they listed any other major, they were considered a non-computing major. Similarly, the dependent variable measuring career interest in computing and technology aggregated the 64 career options on the survey into a dichotomous variable that represented students’ interest either in a career in computing and technology (which included “computer programmer/developer,” “computer systems analyst,” or “web designer”) or an interest in any other career.

Independent variables for both regressions were selected and blocked based on SCCT [34–36] (see Appendix Table A.1). The person inputs block included both personal traits and values, and

included self-reported social identities (gender², race/ethnicity³, first-generation status), as well as students’ belief that programming is important for most careers. The block representing background contextual affordances controlled for additional factors that might influence students’ goals and beliefs [34], and included measures of family income, parent education, and whether or not students had at least one parent in a STEM profession. The learning experiences block consisted of measures of academic achievement in high school, such as GPA, SAT/ACT score(s), and time spent writing computer code. This block also included our key independent variables of interest: the three dichotomous measures indicating whether students self-reported having taken APCSA, APCSP, or both APCS courses.

The self-efficacy block included measures of students’ confidence in their computer programming skills, as well as constructs measuring their academic self-concept, science self-efficacy, and science identity, among others. The outcome expectations block captured students’ beliefs about what might happen should they make certain major or career choices, and it was the only block that differed between the models. In the regression predicting students’ probable major, we used students’ confidence that they would remain in their current major of interest, whereas the model examining students’ career aspirations included a measure representing students’ confidence that they would maintain their current career plans.

Variables in the interests block included measures representing students’ reasons for attending college, such as to make more money or to gain an appreciation of ideas. We also used a construct representing students’ social agency, or the degree to which students are invested in the social welfare of others, as well as measures indicating students’ interest in raising a family, identification as artists, or as goal-driven strivers. The contextual influences block included institutional characteristics, such as a measure of institutional selectivity and whether the college is public or private. Finally, we also controlled for students’ educational degree aspirations. In sum, SCCT guided our selection of independent variables and enabled us to examine the predictive power of APCS courses in light of variables understood to predict major and career choice, thus distinguishing this study from related research conducted by the College Board [68].

4.3.1 Constructs and Factor Analysis. To reduce the number of observed variables and to capture unobserved latent constructs, we performed exploratory factor analysis using principal axis factoring with Promax rotation. These analyses were based on factors used in prior research on undergraduate computing major choice [56] and the impact of college on students [54]. All factors met the reliability thresholds of a Cronbach’s alpha of .65 or higher, and items had individual factor loadings greater than .4. We also made use of existing CIRP constructs developed and validated by researchers at the Higher Education Research Institute [17]. These constructs were developed using item response theory, and thus we do not report Cronbach’s alpha or factor loadings for these items [60]. Further descriptions of factors and constructs and the individual items therein can be found in Appendix Table A.1.

4.3.2 Missing Data. We used the multiple imputation procedures in SPSS 25 to address missing data. Multiple imputation is currently the most robust method when data is not missing at random [10]. The procedure involved making a predetermined number of imputations or estimates

²The TFS asks students to identify as either male or female. In this article, we refer to respondents as men or women as an indication of gender identity rather than biological sex, despite the fact that this variable likely does not capture all students who identify as men or women or any gender identities beyond this binary.

³The TFS aggregates students’ self-selected racial identities into seven broad categories (shown in Appendix A). We recognize that these groupings may reveal racial/ethnic trends in our data while simultaneously obfuscating any heterogeneity that exists within each group and among individuals who do not identify with any of the racial/ethnic groups named in the survey.

Fig. 2. Percentage of first-year undergraduate sample planning to major in computing, by gender, race, and AP course-taking, fall 2017.

for each missing value based on existing values in the dataset, then pooling all of the estimates to account for bias in the estimates. Demographic characteristics and our dependent variables were not imputed but were included in imputation models to aid in predicting values of other missing variables. Results reported in Tables 1 and 2 are based on the pooled estimates across 50 imputations. Although there is currently no way to pool estimates of commonly reported fit indices for logistic regression (e.g., pseudo R-squared, Hosmer-Lemeshow), indices for all 50 imputations are available upon request.

4.4 Descriptive Analysis

To address our first research question, cross tabulations were run to compare the percentage of students who indicated interest in pursuing computing majors or careers as it varied by whether they took APCSA only, APCSP only, both APCS courses, or neither APCS course. This analysis was conducted separately by gender and race/ethnicity (Figures 2 and 3).

4.5 Regression Analysis

To address our second research question and its subparts, we ran one logistic regression to estimate the relationship between APCS course-taking and first-year college students' interest in majoring in computing (see Table 1) and another logistic regression to explore students' career aspirations (see Table 2). For each regression, we first ran a main effects model (Model 1) that controlled for a variety of possible determinants and influences on the dependent variables. We then ran a model that included the main effects and 18 interaction terms (i.e., each of the five race/ethnicity variables by the three AP course variables; gender by the three AP course variables) (Model 2).

5 RESULTS

5.1 Research Question 1: Descriptive Results

Our first research question focused on how taking APCSA, APCSP, or both APCS courses corresponds with entering college students' interest in pursuing computing majors and careers across

Fig. 3. Percentage of first-year undergraduate sample planning to pursue a career in computing, by gender, race, and AP course-taking, fall 2017.

categories of gender and race/ethnicity. As shown in Figure 2, interest in pursuing a computing major among all students was highest among those who took both APCS courses (37.5%), followed by students who took APCS only (28.2%), those who took APCSP only (16.7%), and those who took neither APCS course (3.1%). This general pattern held across gender and racial/ethnic groups.

A similar pattern emerged with respect to interest in a computing career (see Figure 3), as interest among all students was highest among those who took both APCS courses (31.2%), followed by those who took APCS only (23.2%), those who took APCSP only (16.7%), and those who took neither APCS course (3.1%). Once again, this pattern generally held across gender and racial/ethnic identities.

5.2 Research Question 2: Regression Results

The results presented thus far reveal, not surprisingly, a higher degree of interest in computing majors and careers among students who took APCS courses, with even more interest among those who took APCS only or both APCS courses. An important question is whether these associations hold once we accounted for the full range of independent variables included in this study. As such, we now turn to research question 2.

In presenting these results, we focus primarily on how the three APCS variables predicted major and career aspirations, but because the role of APCS course-taking must be understood in the context of which *other* variables were significant, we begin with an overview of such variables. Further, because we found a high degree of overlap in the variables significant in both the major and career regressions, the following section summarizes key findings across both models. In Table 1 (major) and Table 2 (career), significant main effects are shown in Model 1, whereas interaction effects are presented in Model 2. Given our large sample size, we only discuss variables significant at $p < .01$.

5.2.1 Significant Findings Across Major and Career Aspiration Regressions. Across both models, the likelihood of planning to pursue a computing major or career was greater among students who identified as men, Asian, Black, Hispanic, or multi-racial. Coming from a lower-income family or having at least one parent with a STEM career also predicted an increased interest in computing majors and careers. Computing aspirations were significantly lower among students who intended

Table 1. Logistic Regression Predicting Intent to Major in CS Versus All Other Majors ($n = 129,241$)

Variable	Model 1				Model 2			
	b		SE	Exp(B)	b		SE	Exp(B)
<i>Person Inputs</i>								
Sex: Female	-0.728	**	0.036	0.483	-0.903	**	0.042	0.405
<u>Race/Ethnicity (vs. White)</u>								
American Indian	-0.269		0.464	0.764	-0.337		0.526	0.714
Asian	0.744	**	0.041	2.105	0.939	**	0.049	2.556
Black	0.647	**	0.062	1.909	0.654	**	0.068	1.924
Hispanic	0.371	**	0.066	1.449	0.377	**	0.072	1.459
Two or more races	0.173	**	0.053	1.189	0.244	**	0.063	1.277
Another race/ethnicity	0.397	**	0.177	1.488	0.403	**	0.179	1.496
Understanding of computer programming is important	0.089	**	0.017	1.093	0.089	**	0.017	1.093
<i>Background Contextual Affordances</i>								
Family income	-0.104	**	0.020	0.901	-0.101	**	0.020	0.904
First-generation college student	0.053		0.050	1.054	0.056		0.050	1.057
At least one parent in a STEM career	0.103	*	0.034	1.108	0.104	*	0.034	1.109
<i>Learning Experiences</i>								
High school GPA	0.033		0.020	1.033	0.035		0.020	1.036
Number of non-CS AP math/science courses taken	-0.152	**	0.019	0.859	-0.143	**	0.018	0.867
Took only APCSA	0.321	**	0.047	1.379	0.367	**	0.064	1.444
Took only APCSP	0.151		0.076	1.163	0.107		0.117	1.113
Took both APCS courses	0.638	**	0.090	1.893	0.701	**	0.130	2.016
In past year: Written computer code	0.517	**	0.015	1.676	0.505	**	0.015	1.657
Composite ACT score	0.163	**	0.028	1.177	0.159	**	0.028	1.173
<i>Self-Efficacy</i>								
Self-rated: Computer programming skills	0.666	**	0.020	1.947	0.672	**	0.020	1.957
Academic Self-Concept ^a	-0.021		0.022	0.979	-0.021	**	0.022	0.979
Social Self-Concept ^a	-0.219	**	0.019	0.803	-0.221	**	0.019	0.802
Science Self-Efficacy ^a	-0.077	**	0.022	0.926	-0.080	**	0.022	0.923
Science Identity ^a	0.203	**	0.021	1.225	0.198	**	0.021	1.219
Pluralistic Orientation ^a	0.039		0.018	1.039	0.041	**	0.018	1.042
Habits of Mind ^a	-0.059	*	0.020	0.943	-0.059	*	0.020	0.943
<i>Outcome Expectations</i>								
Likelihood of staying in major field	0.093	**	0.018	1.098	0.095	**	0.018	1.100
<i>Interests</i>								
Attending college to be able to get a better job	0.012		0.019	1.012	0.013		0.019	1.013
Attending college to be able to make more money	0.109	**	0.020	1.115	0.105	**	0.020	1.111
Attending college to get training for a specific career	0.077	**	0.018	1.081	0.077	**	0.018	1.080

(Continued)

Table 1. Continued

Variable	Model 1			Model 2				
	b		SE	Exp(B)	b		SE	Exp(B)
Attending college to gain a general education and appreciation of ideas	−0.015		0.015	0.985	−0.014		0.015	0.986
Social Agency ^a	−0.075	**	0.021	0.928	−0.079	**	0.021	0.924
Artist Personality ^a	−0.114	**	0.019	0.892	−0.114	**	0.019	0.892
Striver Personality ^a	−0.041		0.020	0.959	−0.040		0.020	0.961
Goal: Raising a family	−0.079	**	0.017	0.924	−0.073	**	0.018	0.930
<i>Contextual Influences</i>								
Selectivity of institution	0.103	**	0.024	1.109	0.090	**	0.024	1.094
Institution type: Four-year (vs. university)	0.036		0.042	1.036	0.033		0.042	1.033
Institution control: Public (vs. private)	0.173	**	0.037	1.189	0.181	**	0.037	1.199
Concern about ability to finance college education	−0.030		0.017	0.970	−0.027		0.017	0.973
<i>Choice Goals</i>								
<u>Degree Aspirations (vs. BA)</u>								
PhD	−1.024	**	0.051	0.359	−1.014	**	0.051	0.363
Law	−1.286	**	0.127	0.276	−1.283	**	0.127	0.277
Medical	−2.658	**	0.118	0.070	−2.647	**	0.118	0.071
Master's/MDiv	−0.283	**	0.037	0.753	−0.282	**	0.037	0.754
Other	−0.830	**	0.202	0.436	−0.822	**	0.200	0.440
<i>Interaction Terms</i>								
Female x APCSA					0.713	**	0.087	2.040
Female x APCSP					0.517	**	0.155	1.677
Female x Both APCS courses					0.768	**	0.197	2.156
American Indian x APCSA					0.163		1.686	1.176
American Indian x APCSP					−17.985		40,192.9	0
American Indian x Both APCS courses					0.800		2.000	0.689
Asian x APCSA					−0.583	**	0.087	0.558
Asian x APCSP					−0.393		0.176	0.675
Asian x Both APCS					−0.750	**	0.196	0.472
Black x APCSA					0.065		0.194	1.067
Black x APCSP					0.154		0.301	1.167
Black x Both APCS					0.061		0.364	1.063
Hispanic x APCSA					0.170		0.195	1.185
Hispanic x APCSP					0.228		0.252	1.256
Hispanic x Both APCS					−0.504		0.398	0.604
Two or more races x APCSA					−0.271		0.132	0.763
Two or more races x APCSP					−0.298		0.241	0.742
Two or more races x Both APCS courses					−0.089		0.280	0.915

b=regression coefficient in log-odds; SE=standard error of the coefficient; Exp(B)=odds ratios.

^aLatent construct; see Appendix Table A.1.

* $p < .01$. ** $p < .001$.

Table 2. Logistic Regression Predicting Career Aspirations in Computing and Technology Versus All Other Careers ($n = 129,241$)

Variable	Model 1			Model 2				
	b		SE	Exp(B)	b		SE	Exp(B)
<i>Person Inputs</i>								
Sex: Female	-0.809	**	0.041	0.445	-1.001	**	0.048	0.368
<u>Race/Ethnicity (vs. white)</u>								
American Indian	-0.292		0.553	0.747	-0.471		0.695	0.625
Asian	0.646	**	0.045	1.908	0.820	**	0.056	2.271
Black	0.661	**	0.069	1.938	0.697	**	0.075	2.008
Hispanic	0.375	**	0.073	1.455	0.425	**	0.080	1.529
Two or more races	0.204	**	0.058	1.226	0.279	**	0.070	1.322
Another race/ethnicity	0.383		0.197	1.467	0.389		0.199	1.476
Understanding of computer programming is important	0.053	*	0.018	1.055	0.054	*	0.018	1.055
<i>Background Contextual Affordances</i>								
Family income	-0.169	**	0.023	0.844	-0.166	**	0.023	0.847
First-generation college student	0.081		0.055	1.085	0.084		0.055	1.088
At least one parent in a STEM career	0.296	**	0.037	1.344	0.294	**	0.037	1.342
<i>Learning Experiences</i>								
High school GPA	0.055		0.022	1.057	0.058	*	0.022	1.060
Number of non-CS AP math/science courses taken	-0.158	**	0.021	0.854	-0.152	**	0.020	0.859
Took only APCS A	0.238	*	0.051	1.269	0.306	**	0.069	1.359
Took only APCSP	0.181		0.081	1.199	0.107		0.125	1.186
Took both APCS courses	0.520	**	0.094	1.682	0.457	*	0.136	1.580
In past year: Written computer code	0.508	**	0.016	1.662	0.497	**	0.016	1.644
Composite ACT score	0.160	**	0.031	1.174	0.158	**	0.031	1.171
<i>Self-Efficacy</i>								
Self-rated: Computer programming skills	0.665	**	0.023	1.945	0.668	**	0.023	1.950
Academic Self-Concept ^a	-0.052		0.024	0.949	-0.053		0.024	0.948
Social Self-Concept ^a	-0.251	**	0.021	0.778	-0.253	**	0.021	0.776
Science Self-Efficacy ^a	-0.090	**	0.024	0.914	-0.092	**	0.024	0.912
Science Identity ^a	0.249	**	0.024	1.283	0.244	**	0.024	1.277
Pluralistic Orientation ^a	0.066	*	0.020	1.068	0.069	*	0.020	1.071
Habits of Mind ^a	-0.047		0.022	0.954	-0.047		0.022	0.954
<i>Outcome Expectations</i>								
Likelihood of maintaining career choice	0.017		0.019	1.017	0.021		0.019	1.021
<i>Interests</i>								
Attending college to be able to get a better job	0.039		0.022	1.040	0.040		0.022	1.041
Attending college to be able to make more money	0.102	**	0.020	1.108	0.100	**	0.022	1.105

(Continued)

Table 2. Continued

Variable	Model 1				Model 2			
	b		SE	Exp(B)	b		SE	Exp(B)
Attending college to get training for a specific career	0.162	**	0.020	1.176	0.161	**	0.020	1.174
Attending college to gain a general education and appreciation of ideas	-0.032		0.016	0.969	-0.031		0.016	0.969
Social Agency ^a	-0.089	**	0.023	0.915	-0.093	**	0.023	0.911
Artist Personality ^a	-0.136	**	0.021	0.873	-0.136	**	0.021	0.872
Striver Personality ^a	-0.055		0.022	0.946	-0.053		0.022	0.948
Goal: Raising a family	-0.093	**	0.019	0.911	-0.089	**	0.019	0.915
<i>Contextual Influences</i>								
Selectivity of institution	0.108	**	0.027	1.114	0.096	**	0.027	1.101
Institution type: Four-year (vs. university)	0.019		0.047	1.019	0.016		0.047	1.016
Institution control: Public (vs. private)	0.311	**	0.041	1.365	0.318	**	0.041	1.374
Concern about ability to finance college education	-0.031		0.019	0.970	-0.028		0.019	0.973
<i>Choice Goals</i>								
<u>Degree Aspirations (vs. BA)</u>								
PhD	-0.988	**	0.057	0.372	-0.978	**	0.056	0.376
Law	-1.873	**	0.197	0.154	-1.870	**	0.196	0.154
Medical	-2.429	**	0.123	0.088	-2.424	**	0.123	0.089
Master's/MDiv	-0.242	**	0.041	0.785	-0.242	**	0.041	0.785
Other	-0.863	**	0.233	0.422	-0.847	**	0.232	0.429
<i>Interaction Terms</i>								
Female x APCSA					0.742	**	0.095	2.101
Female x APCSP					0.481	**	0.170	1.617
Female x Both APCS courses					0.849	**	0.211	2.337
American Indian x APCSA					0.594		1.784	1.811
American Indian x APCSP					-17.461		40,192.9	0
American Indian x Both APCS courses					1.301		2.108	3.674
Asian x APCSA					-0.555	**	0.094	0.574
Asian x APCSP					-0.269		0.188	0.764
Asian x Both APCS					-0.333	**	0.204	0.716
Black x APCSA					-0.128		0.209	0.880
Black x APCSP					0.170		0.317	1.185
Black x Both APCS					-0.282		0.398	0.754
Hispanic x APCSA					-0.127		0.215	0.881
Hispanic x APCSP					-0.006		0.278	0.994
Hispanic x Both APCS					-0.338		0.427	0.713
Two or more races x APCSA					-0.248		0.141	0.780
Two or more races x APCSP					-0.497		0.269	0.609
Two or more races x Both APCS courses					0.080		0.297	1.083

b=regression coefficient in log-odds; SE=standard error of the coefficient; Exp(B)=odds ratios.

^aLatent construct; see Appendix Table A.1.

* $p < .01$. ** $p < .001$.

to earn graduate/professional degrees, reported higher social self-concept, or who held stronger values and orientations around social agency, the arts, or family. Goals and values that were more predictive of aspirations for computing majors and careers included attending college with the goal of making more money or to get training for a specific career. Not surprisingly, many of these significant variables aligned with findings in prior research exploring CS major aspirations using similar TFS data [56].

Most of the additional variables that were significant across both regressions represented aspects of learning experiences and self-efficacy that were not available in the prior study using these data [56] but relate specifically to the computing and STEM domain. For example, reporting higher self-ratings of computing skills or having written computer code frequently in the past year predicted greater interest in computing majors and careers. More broadly, results revealed greater interest in computing majors and careers among students who reported higher levels of science identity but lower levels of science self-efficacy. In addition, greater numbers of AP math and AP science courses taken—other than APCS—negatively predicted interest in computing majors and careers, suggesting that students who take a broader range of advanced STEM courses in high school are less inclined to pursue computing majors and careers.

We now turn to the main focus of the present study, which is the extent to which taking APCS courses predicts first-year college students' major or probable career, above and beyond the effects associated with other variables in the model. Further, we examined how gender or race/ethnicity moderated the relationships between taking one or both APCS courses and students' interest in computing majors and careers.

5.2.2 APCS Course-Taking Predicting Computing Major. The logistic regression predicting intent to major in computing (see Table 1) revealed differences in the salience of our three APCS variables (taking only APCSA, only APCSP, or both APCS courses). As shown in the main effects model (Model 1), students who took only APCSA were 38% more likely to indicate CS as their probable major (odds ratio: 1.379) than those who took no APCS courses, even when controlling for other relevant blocks of variables (Person Inputs, Background Contextual Affordances, Learning Experiences, etc.). Similarly, students who took both APCSA and APCSP were 89% more likely (odds ratio: 1.893) than students who took no APCS courses to indicate intent to major in CS. However, taking only APCSP was not a significant predictor of intent to major in CS.

5.2.2.1 Major by Gender Interactions. After running the main effects model, we tested whether relationships between taking APCS courses and majoring in computing were moderated by students' gender, seeking here to understand if the predictive power of APCS courses might differ between women and men. As shown in Model 2 of Table 1, all three interactions were significant. In other words, taking APCSA, APCSP, or both APCS courses were all more positively associated with women's aspirations to major in computing than they were for men. Notably, given that taking only APCSP was not significant in the main effects model, the interaction with gender suggests that taking the course was uniquely associated with women's intent to major in computing.

5.2.2.2 Major by Race/Ethnicity Interactions. As shown in Model 2 of Table 1, there were two significant interactions between APCS course-taking and students' racial and ethnic identities. Although taking only APCSA was a positive predictor of students' intentions to pursue a CS major for all students generally, the significant interaction term indicated that APCSA was a more salient predictor of majoring in computing for white students than for Asian students. We also found that taking both APCS courses was a stronger positive predictor of pursuing a major in CS for white students than for Asian students.

5.2.3 APCS Course-Taking Predicting Computing or Technology Career Aspirations. Using the same independent variables as in the preceding analysis of major aspirations, we ran two models to predict students’ aspirations to work in computing or technology fields versus all other career options (see Table 2). Similar to the findings predicting students’ intent to major in computing, Model 1 shows that taking only APCSA or both APCS courses positively predicted students’ interest in a computing career (although less so than these courses predicted students’ interest in a computing major). As shown in Table 2, students who took only APCSA were 27% more likely to indicate a probable career in computing (odds ratio: 1.269) than students who did not take any APCS courses. Students who took both APCSA and APCSP were 68% more likely (odds ratio: 1.682) than students who did not take any APCS courses to indicate aspirations to work in computing and technology. Notably, taking only APCSP did not significantly predict students’ interest in pursuing a computing career.

5.2.3.1 Career by Gender Interactions. We also explored whether the association between APCS course-taking and students’ career aspirations was moderated by students’ gender. We ran three cross-product interactions between each APCS course-taking variable and the gender variable. As shown in Model 2 of Table 2, all three interactions were significant. In other words, taking APCSA, APCSP, and both APCS courses appeared to have a stronger positive association with women’s computing career aspirations than with those of men. Although the main effect of taking only APCSP was not significant in predicting computing career aspirations, the significant interaction term suggests that APCSP may play a role in encouraging computing career interests for women in particular.

5.2.3.2 Career by Race/Ethnicity Interactions. We also used interaction terms to explore whether the predictive power of taking any of the APCS course offerings on computing career aspirations was moderated by students’ race or ethnicity. As seen in Table 2, only one of the interaction terms emerged as significant in predicting a student’s computing career aspirations. Specifically, the positive association between taking only APCSA and students’ aspirations to work in computing and tech was stronger among white students than among Asian students.

6 DISCUSSION

Interpretations of these findings depend on how one perceives the purpose of APCS courses. If these courses are viewed strictly as the primary entry point in the computing pipeline, scholars have already found that the addition of APCSP appears to have contributed to broadening participation by increasing the number of students who are taking at least one APCS course [13]. However, our study examined first-year college students’ longer-term commitment to computing by assessing whether APCS course-taking was associated with aspirations to pursue degrees or careers in computing fields. After controlling for the predictive power of nearly three dozen variables reflecting different facets of SCCT, the results revealed that taking the traditional APCSA course, whether alone or in addition to APCSP, was associated with an increased likelihood of planning to major in or pursue careers in computing. However, taking only APCSP—although positively *correlated* with computing major and career choice based on the descriptive analysis—did not remain a significant predictor of these outcomes once the full range of independent variables was controlled.

Our findings did, however, suggest gender and racial/ethnic variations in the predictive power of APCS courses on students’ computing majors and career intentions. For example, taking any of these courses (APCSA, APCSP, or both APCS courses) was more strongly associated with women’s plans to pursue computing majors and careers than was the case for men. The finding regarding APCSP is especially noteworthy, as taking only APCSP was not predictive of computing

intentions for our full sample. Thus, it is possible that the experience of taking APCS courses—including APCSP—uniquely encourages high school girls to consider computing pathways. Although causality cannot be determined from these data, it is worth noting that the College Board [68] reported a similar finding with respect to gender, albeit with a more limited set of control variables. Further, our race/ethnicity interactions revealed that taking APCSA (whether alone or in addition to APCSP) related more strongly to longer-term computing intentions for white students than for Asian students. Taking APCSP on its own, however, did not yield any differences in predictive power by students' race/ethnicity. In other words, across all racial/ethnic groups, computing major and career aspirations appeared unrelated to APCSP course-taking when the full range of variables were controlled.

7 LIMITATIONS

It is important to acknowledge several limitations to this study. First, our sample was restricted to first-time, full-time undergraduate students attending the 168 four-year colleges and universities that participated in the 2017 TFS. Therefore, findings may not reflect the experience of APCS course-takers who attended community colleges or other non-participating institutions, who were enrolled part-time, or who did not enter college in fall 2017. Our analyses would have benefited from a more representative sample of institutions that included two-year colleges, as community colleges can be a critical site of preparation for students who eventually earn degrees in computing [8, 37]. Further, only a small number (9%) of U.S. public or private high schools even offered APCSP in the 2016–2017 school year, narrowing the sample of students [16].

Second, our data were cross sectional, such that information on students' prior APCS course-taking was collected at the same time as their major and career intentions were measured. Therefore, we cannot say whether or to what extent the APCS courses *led* to students' interests in computing majors or careers. Indeed, it is likely that prior interest in computing led certain students to enroll in APCS. As such, despite the number of control variables included in this study, we could not account for self-selection bias and causality could not be determined. In addition, the cross-sectional nature of the data means that career and major aspirations were measured only at the point of college entry, despite the reality that students' interest in pursuing computing fields may change significantly during college [33, 55]. Relatedly, this study did not account for the fact that many students who pursue non-computing majors and careers actually incorporate computing concepts in their chosen fields (bioinformatics, geoinformatics, etc.); this level of nuance could not be gleaned from the data used in this study.

Third, the sample only reflected students who had taken APCS courses prior to entering college in fall 2017. This time frame represents just 1 year after the official roll-out of APCSP in 2016–2017, although some students may have taken APCSP even earlier during the 2-year pilot phase. Thus, this study reflects the early stages of the APCSP course and does not account for changes that may have occurred in course content or delivery as more schools have adopted the course, as enrollments have continued to grow, and as instructors may have evolved their pedagogical approaches. We also do not know from these data the specific year in which students enrolled in APCS courses, nor which course they took first if they took both APCSA and APCSP.

A final set of limitations relates to the variables that were or were not included in our study. First, not all elements of SCCT are represented by the variables we included. Second, although SCCT has been widely used as a career development framework, we might also question whether it adequately speaks to the experiences and pathways of all students, especially those who do not follow prescriptive and normative school-to-career pathways. Including other variables into our model or using a different framework might have yielded contrasting results. Finally, our use of a relatively large number of control variables suggests that our regression results may be a

conservative estimate of the association between APCSP course-taking and computing major and career intentions. In particular, we suspect that the distinction between our study’s findings and that of the College Board [68] (as it relates to the predictive power of APCSP) results from our inclusion of a larger range of covariates, including students’ computing experiences and self-efficacy.

8 DIRECTIONS FOR FUTURE RESEARCH

The limitations described previously point the way to important new directions for future research on the role of APCS courses and how students’ interests in computing majors and careers develop. First, it is important to engage in research that deepens our understanding of what leads high school teachers and advisors to recommend that students take one APCS course over another, and specifically to learn whether the current two-course APCS structure might, perhaps unintentionally, cause some students to be “tracked” to a particular APCS course based on assumptions of ability or course rigor. If APCSA portends longer-term retention in the computing pipeline, more so than APCSP, analyses of who takes which APCS course when both are offered (and which course they take first) would help us consider the extent to which inequities are being reproduced in practice. This is especially important in light of the fact that taking APCSP positively correlates with computing aspirations among women, but it does not appear to boost computing major or career interests among students of color in particular.

With respect to students taking both APCS courses, this study showed that they had a much higher likelihood of intending to pursue computing majors and careers than students taking either APCSA or APCSP alone. The recent College Board report [68] conveys a similar finding. We believe that a deeper understanding of students who take both courses would add significant value to BPC efforts. Although both courses are considered introductory computing classes—and some assume that APCSP serves as a precursor to the more programming-focused APCSA course—it is possible for students to enroll in the two classes concurrently, something that ambitious college-going aspirants with access to both courses might elect to do, for the aforementioned benefits of augmenting high school transcripts with AP courses.

Next, future research should examine how many and which groups of students take APCS courses in various settings and formats. Our preliminary analyses of TFS respondents’ high school IDs showed that some students who reported having taken APCSP attended schools that did not offer the course, at least not as indicated by the College Board.⁴ Students may have taken APCSP online, at other schools, or as an independent study. Ideally, future research on APCS would account for variations in course format while also considering the characteristics of schools offering the course, as well as information on course instructors and their pedagogical approaches. Adding such nuance to a study like the present one could shift, or at least better contextualize, our conclusions about APCSP course-takers’ career and major aspirations.

Importantly, scholars aimed at determining causal connections between APCS courses and student outcomes would benefit from data that better account for myriad reasons that students enroll in these courses. Although our models controlled for students’ motivations for attending college and for their major/career choices, the TFS data did not include students’ own reasons for enrolling in APCS courses. Possible reasons include a desire to gain valuable skills in their ultimate quest for computing degrees, develop an understanding of basic computing concepts, and/or learn about the broader role of computing in society. Students’ motivations for enrolling may also be highly dependent upon advice of teachers, counselors, family members, or peers. Further examination into students’ reasons for taking APCS courses, how these vary among students taking APCSA,

⁴This observation is based on supplemental analyses we conducted by matching the survey respondents’ high school IDs with data provided to us by the College Board on which schools offered APCSP between fall 2013 and spring 2017.

APCSP, or both courses, and how they differ by students' gender, race/ethnicity, and other traits such as family income, high school type (private vs. public), and academic achievement (e.g., high school GPA, number of AP courses taken) would enable researchers to better assess the effectiveness of these courses as part of broader diversification efforts in computing. Additionally, prior research [50, 51, 61] has also suggested that once enrolled in an introductory computing course, students' motivations and aspirations to major or work in a computing field may change in response to course content and pedagogy. A better understanding of how and why these aspirations change and for whom may shed light on pedagogical approaches, activities, and content that can help maintain student interest.

Finally, research on the role of APCS courses would also ideally follow students' pathways beyond the point of college entry and consider students' use of computing concepts in their non-computing majors and careers. In doing so, researchers might also consider outcomes beyond those frequently associated with the pipeline metaphor (i.e., major or career intentions), as well as include others, such as the desire to develop an appreciation of technology in society or develop confidence or self-efficacy in programming. Researchers might also think even further out of the box by examining the potential of APCS courses to encourage a sense of agency and empowerment among students, especially for historically minoritized populations [52].

9 CONCLUSION

APCSP represents an important effort by educators, the College Board, and technology industry leaders to broaden the diversity of high school students who understand foundational computing concepts, appreciate the role of technology in society, and ultimately may seek further education and careers in computing fields. Its introduction several years ago marked a critical acknowledgment that to diversify computing in the United States, CS instruction needs to extend beyond the primarily coding-based emphasis of the traditional APCSA course. This study sought to understand the extent to which having taken one or both these APCS courses is associated with entering college students' interest in computing majors and careers. Our findings suggested a significant correlation between APCSA and longer-term computing aspirations, but that taking APCSP on its own was not predictive of students' intentions to major or seek employment in computing, at least when we accounted for the full range of control variables. However, we did find that taking APCS courses was significantly more predictive of women's interests in computing-related majors and careers than those of men, and that APCSP did predict women's longer-term computing interests despite the fact that it was not significant for the full sample nor for students of color in particular.

Although the findings raise a number of questions for educators and the College Board regarding who takes which course and why, consideration of these courses ought not exist in a vacuum. Indeed, discussions on the role of APCS courses must consider that both systems of education and CS as a field reside within and replicate broader systems of oppression such as sexism, racism, and other forms of exclusion [6, 20, 49, 52] and that technological innovations made by computer scientists have further amplified racial hierarchies by hiding, accelerating, and deepening discrimination under a guise of neutrality [7, 48]. As such, APCSP is not—and should not be expected to be—a panacea for the structural oppressions that persist in schooling and likely in computing courses. Further, the true value of APCSP and other diversity and inclusion efforts cannot be measured solely within the school-career computing pipeline paradigm. Thus, rather than considering APCS courses within a fixed and narrow vocational pathway, it is important to explore how the pipeline itself serves to exclude students, particularly students of color. Expansive efforts to re-envision and transform computing education environments in the United States and elsewhere where broadening participation in computing is a concern must attend to how all students can be better welcomed into and supported in computing courses.

A APPENDIX

A.1 Variable List and Coding

Table A.1.

Variable	Coding	% Missing
Personal Characteristics		
Female (Reference Category: Male)	Dichotomous: 0 = “Male,” 1 = “Female	0.2
<i>Race/Ethnicity (Reference Category: White)</i>		
American Indian	Dichotomous: 0 = “No,” 1 = “Yes”	0.3
Asian	Dichotomous: 0 = “No,” 1 = “Yes”	0.3
Black	Dichotomous: 0 = “No,” 1 = “Yes”	0.3
Hispanic	Dichotomous: 0 = “No,” 1 = “Yes”	0.3
Multiracial	Dichotomous: 0 = “No,” 1 = “Yes”	0.3
Other	Dichotomous: 0 = “No,” 1 = “Yes”	0.3
A basic understanding of computer programming is important for nearly any career today	4-point scale: 1 = “Strongly Disagree” to 4 = “Strongly Agree”	8.6
Background Characteristics		
Family income	12-point scale: 1 = “Less than \$15,000” to 12 = “\$500,000 or more”	6.7
First-generation college student	Dichotomous: 0 = “No,” 1 = “Yes”	2.8
At least one parent in a STEM career	Dichotomous: 0 = No parent in STEM career, 1 = At least 1 parent in STEM (physician, engineer, health professional, nurse, research scientist, IT professional, or secondary STEM teacher)	0
Learning Experiences		
High school GPA	5-point scale: 1 = “B– or below” to 5 = “A or A+”	0.6
Number of non-CS AP math/science courses taken	7-point scale: 0 = 0 other AP Math or Science courses to 6 = 6 other AP Math or Science courses	0
Took only AP Computer Science A	Dichotomous: 0 = “No,” 1 = “Yes”	12.3
Took only AP Computer Science Principles	Dichotomous: 0 = “No,” 1 = “Yes”	12.3
Took both AP Computer Science Courses	Dichotomous: 0 = “No,” 1 = “Yes”	12.3
In past year: Written computer code	3-point scale: 1 = “Not at all,” 2 = “Occasionally,” 3 = “Frequently”	2.4
ACT Composite Score ^a	36-point scale	20.8
Self-Efficacy		
Self-rated computer programming skills	5-point scale: 1 = “Lowest 10%” to 5 = “Highest 10%”	5.7
<i>Academic Self-Concept^b</i>	<i>Four-item construct</i>	5.3
Self-rating: Academic ability	5-point scale: 1 = “Lowest 10%” to 5 = “Highest 10%”	
Self-rating: Drive to achieve	5-point scale: 1 = “Lowest 10%” to 5 = “Highest 10%”	

(Continued)

Variable	Coding	% Missing
Self-rating: Mathematic ability	5-point scale: 1 = "Lowest 10%" to 5 = "Highest 10%"	5.6
Self-rating: Intellectual self-confidence	5-point scale: 1 = "Lowest 10%" to 5 = "Highest 10%"	
<i>Social Self-Concept^b</i>	<i>Three-item construct</i>	
Self-rating: Leadership ability	5-point scale: 1 = "Lowest 10%" to 5 = "Highest 10%"	
Self-rating: Public speaking ability	5-point scale: 1 = "Lowest 10%" to 5 = "Highest 10%"	
Self-rating: Social self-confidence	5-point scale: 1 = "Lowest 10%" to 5 = "Highest 10%"	4.0
<i>Science Self-Efficacy^b</i>	<i>Ten-item construct</i>	
Can use technical science skills (use of tools, instruments, and/or techniques)	5-point scale: 1 = "Not at all" to 5 = "Absolutely"	
Can generate a research question	5-point scale: 1 = "Not at all" to 5 = "Absolutely"	
Can determine how to collect appropriate data	5-point scale: 1 = "Not at all" to 5 = "Absolutely"	
Can explain the results of a study	5-point scale: 1 = "Not at all" to 5 = "Absolutely"	
Can use scientific literature to guide research	5-point scale: 1 = "Not at all" to 5 = "Absolutely"	
Can integrate results from multiple studies	5-point scale: 1 = "Not at all" to 5 = "Absolutely"	
Can ask relevant questions	5-point scale: 1 = "Not at all" to 5 = "Absolutely"	
Can identify what is known and not known about a problem	5-point scale: 1 = "Not at all" to 5 = "Absolutely"	
Can understand scientific concepts	5-point scale: 1 = "Not at all" to 5 = "Absolutely"	
Can see connections between different areas of science and mathematics	5-point scale: 1 = "Not at all" to 5 = "Absolutely"	11.0
<i>Science Identity^b</i>	<i>Four-item construct</i>	
I have a strong sense of belonging to a community of scientists	5-point scale: 1 = "Strongly disagree" to 5 = "Strongly agree"	
I derive great personal satisfaction from working on a team that is doing important research	5-point scale: 1 = "Strongly disagree" to 5 = "Strongly agree"	
I think of myself as a scientist	5-point scale: 1 = "Strongly disagree" to 5 = "Strongly agree"	
I feel like I belong in the field of science	5-point scale: 1 = "Strongly disagree" to 5 = "Strongly agree"	2.2
<i>Pluralistic Orientation^b</i>	<i>Five-item construct</i>	
Self-rating: Ability to see the world from someone else's perspective	5-point scale: 1 = "A major weakness" to 5 = "A major strength"	

(Continued)

Variable	Coding	% Missing
Self-rating: Tolerance of others with different beliefs	5-point scale: 1 = “A major weakness” to 5 = “A major strength”	
Self-rating: Openness to having my own views challenged	5-point scale: 1 = “A major weakness” to 5 = “A major strength”	
Self-rating: Ability to discuss and negotiate controversial issues	5-point scale: 1 = “A major weakness” to 5 = “A major strength”	
Self-rating: Ability to work cooperatively with diverse people	5-point scale: 1 = “A major weakness” to 5 = “A major strength”	
<i>Habits of Mind^b</i>	<i>Nine-item construct</i>	2.7
Frequency in past year: Ask questions in class	3-point scale: 1 = “Not at all,” 2 = “Occasionally,” 3 = “Frequently”	
Frequency in past year: Support your opinions with a logical argument	3-point scale: 1 = “Not at all,” 2 = “Occasionally,” 3 = “Frequently”	
Frequency in past year: Seek solutions to problems and explain them to others	3-point scale: 1 = “Not at all,” 2 = “Occasionally,” 3 = “Frequently”	
Frequency in past year: Take a risk because you feel you have more to gain	3-point scale: 1 = “Not at all,” 2 = “Occasionally,” 3 = “Frequently”	
Frequency in past year: Seek alternative solutions to a problem	3-point scale: 1 = “Not at all,” 2 = “Occasionally,” 3 = “Frequently”	
Frequency in past year: Look up scientific research articles and resources	3-point scale: 1 = “Not at all,” 2 = “Occasionally,” 3 = “Frequently”	
Frequency in past year: Explore topics on your own, even though it was not required for class	3-point scale: 1 = “Not at all,” 2 = “Occasionally,” 3 = “Frequently”	
Frequency in past year: Accept mistakes as part of the learning process	3-point scale: 1 = “Not at all,” 2 = “Occasionally,” 3 = “Frequently”	
Frequency in past year: Take on a challenge that scares you	3-point scale: 1 = “Not at all,” 2 = “Occasionally,” 3 = “Frequently”	
Outcome Expectations		
Likelihood of maintaining major choice	4-point scale: 1 = “Very good chance” to 4 = “No chance”	13.1
Likelihood of maintaining career choice	4-point scale: 1 = “Very good chance” to 4 = “No chance”	13.2
Interests		
Reason to attend college: Get a better Job	3-point scale: 1 = “Not Important,” 2 = “Somewhat Important,” 3 = “Very Important”	4.6
Reason to attend college: Make more money	3-point scale: 1 = “Not Important,” 2 = “Somewhat Important,” 3 = “Very Important”	4.8
Reason to attend college: Training for a specific career	3-point scale: 1 = “Not Important,” 2 = “Somewhat Important,” 3 = “Very Important”	4.9
Reason to attend college: Gain general education and appreciation of ideas	3-point scale: 1 = “Not Important,” 2 = “Somewhat Important,” 3 = “Very Important”	4.7

(Continued)

Variable	Coding	% Missing
<i>Social Agency^b</i>	<i>Six-item construct</i>	12.2
Goal: Keeping up to date with political affairs	4-point scale: 1 = "Not important" to 4 = "Essential"	
Goal: Participating in a community action program	4-point scale: 1 = "Not important" to 4 = "Essential"	
Goal: Influencing social values	4-point scale: 1 = "Not important" to 4 = "Essential"	
Goal: Becoming a community leader	4-point scale: 1 = "Not important" to 4 = "Essential"	
Goal: Helping others who are in difficulty	4-point scale: 1 = "Not important" to 4 = "Essential"	
Goal: Helping to promote racial understanding	4-point scale: 1 = "Not important" to 4 = "Essential"	
Contextual Influences		
<i>Artist Personality ($\alpha = .736$)</i>	<i>Four-item construct</i>	13.8
Goal: Becoming accomplished in one of the performing arts	4-point scale: 1 = "Not important" to 4 = "Essential"	
Goal: Creating artistic work	4-point scale: 1 = "Not important" to 4 = "Essential"	
Goal: Writing original works	4-point scale: 1 = "Not important" to 4 = "Essential"	
Self-rating: Artistic ability	5-point scale: 1 = "Lowest 10%" to 5 = "Highest 10%"	
<i>Striver Personality ($\alpha = .667$)</i>	<i>Four-item construct</i>	13.6
Goal: Becoming an authority in my field	4-point scale: 1 = "Not important" to 4 = "Essential"	
Goal: Becoming successful in a business of my own	4-point scale: 1 = "Not important" to 4 = "Essential"	
Goal: Being very well off financially	4-point scale: 1 = "Not important" to 4 = "Essential"	
Goal: Obtaining recognition from my colleagues for contributions to my special field	4-point scale: 1 = "Not important" to 4 = "Essential"	
Goal: Raising a family	4-point scale: 1 = "Not important" to 4 = "Essential"	12.5
Selectivity	Mean score of entering freshmen on the Verbal/Math portions of the SAT or converted ACT	0.3
Four-year (vs. university)	Dichotomous: 0 = University; 1 = Four-year college	0
Public (vs. private)	Dichotomous: 0 = Public, 1 = Private	0
Concern about ability to finance college education	3-point scale: 1 = "None," 2 = "Some," 3 = "Major"	1.2
Choice Goals		
<i>Degree aspirations (Reference Category: Bachelor's)</i>		
PhD	Dichotomous: 0 = All others, 1 = PhD	0

(Continued)

Variable	Coding	% Missing
Law	Dichotomous: 0 = All others, 1 = Law	0
Medicine	Dichotomous: 0 = All others, 1 = Medicine	0
Master’s	Dichotomous: 0 = All others, 1 = Master’s	0
Other	Dichotomous: 0 = All others, 1 = Other	0
Dependent Variables		0
Intent to major in computer science	Dichotomous: 0 = All others, 1 = “Computer science,” “Computer/Management information systems,” or “Other math/computer science”	2.3
Intent to pursue a computing career	Dichotomous: 0 = All others, 1 = “Computer programmer/developer,” “Computer systems analyst,” or “Web designer”	5.5

^aSAT scores were converted to ACT Composite scores for students using 2017 SAT Concordance Tables retrieved from <https://www.act.org/content/act/en/products-and-services/the-act/scores/act-sat-concordance.html>.

^bThese constructs were created and validated by HERI. See Sharkness et al. [60] for details on development and reliability.

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