The Journal of Higher Education

ISSN: 0022-1546 (Print) 1538-4640 (Online) Journal homepage: https://www.tandfonline.com/loi/uhej20

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To cite this article: Linda J. Sax, Kathleen J. Lehman, Jerry A. Jacobs, M. Allison Kanny, Gloria Lim, Laura Monje-Paulson & Hilary B. Zimmerman (2017) Anatomy of an Enduring Gender Gap: The Evolution of Women's Participation in Computer Science, The Journal of Higher Education, 88:2, 258-293, DOI: 10.1080/00221546.2016.1257306

To link to this article: https://doi.org/10.1080/00221546.2016.1257306

Published online: 20 Dec 2016.

THE JOURNAL OF HIGHER EDUCATION
2017, VOL. 88, NO. 2, 258–293
http://dx.doi.org/10.1080/00221546.2016.1257306

Anatomy of an Enduring Gender Gap: The Evolution of Women's Participation in Computer Science

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ABSTRACT

Given growing interest in computing fields, as well as a long-standing gender gap in computer science, this study used nationwide survey data on college students during 4 decades to: (a) document trends in aspirations to major in computer science among undergraduate women and men; (b) explore the characteristics of women and men who choose to major in computer science and how this population has evolved over time; and (c) identify the key determinants of the gender gap in the selection of computer science majors during the past 4 decades. The data included 8 million students attending 1,225 baccalaureate-granting institutions from 1971 to 2011, with selected-year multivariate analyses of 18,830 computer science majors (and 904,307 students from all other majors). The results revealed heavy fluctuations in students' interest in computer science from 1971 to 2011, with trends highlighting a significant downturn between the late 1990s and 2011 as well as a persistent, sizeable underrepresentation of women across all years. The study also showed that while some of the traditional explanations for the gender gap in computer science held true, there have been distinctive shifts in *who* pursues computer science and *why* some students may be particularly interested in or dissuaded from the major.

ARTICLE HISTORY
Received 27 May 2015
Accepted 4 October 2016

KEYWORDS
College; computer science; gender; major selection; STEM

In recent years, women's underrepresentation in science, technology, engineering, and math (STEM) fields has garnered widespread attention in public, academic, and policy circles. President Obama has indicated his commitment to addressing the lack of women in STEM fields through his White House Educate to Innovate Program (The White House, 2013), and he more recently targeted efforts to the field of computer science as part of the Computer Science for All Initiative (The White House, 2016).

Indeed, of all the STEM fields, the gender gap in computer science is among the most apparent. Although women's representation among

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computer science bachelor's degree recipients has fluctuated during the past four decades from a low of 13.6% (in 1971) to a high of 37.1% (in 1984), women presently comprise only 18.0% of computer science graduates (National Center for Education Statistics [NCES], 2014). Concurrent with the declining proportion of women in the field since the mid-1980s, computing and information technology has become a booming industry, underscoring an important national need for individuals with college-level training in computer-related fields (Singh, Allen, Scheckler, & Darlington, 2007). Individuals with such training often go on to work as computer programmers, computer systems analysts, systems engineers, and computer scientists (Bureau of Labor Statistics [BLS], 2014).

The dearth of women in these professions is more than just a matter of numbers, however, as the technology industry and society at large often suffer from inattention to women's needs in the development process. For example, the use of "tech assistants" (e.g., Android's Cortana or Apple's Siri) has been criticized for being ill-equipped to respond to user requests regarding crises that predominantly affect women (e.g., sexual assault; Miner et al., 2016). Similarly, Apple faced heavy criticism in 2014 when its native health application failed to include the ability to track a woman's menstrual cycle (Alba, 2015). Some critics argued that these missteps reflect the male-centered nature of the technology industry (Chemaly, 2016).

To help address such assertions and meet increased demand for trained computer scientists, widespread efforts have encouraged participation in computing fields, especially among women (e.g., Code.org's "Hour of Code" initiative; Google's "Made With Code" campaign; the Girls Who Code organization; the National Center for Women and Information Technology; Code.org, 2013; Dockterman, 2014). While these are positive steps toward increasing participation in computer science, such efforts would be bolstered by an awareness of the backgrounds, characteristics, and personality orientations of students who are most interested in computing. Further, there is no current empirical understanding of whether computer science attracts the same types of women and men today as it has in previous decades.

To address these gaps, this study had three primary aims: (a) to document nationwide trends in aspirations to major in computer science among undergraduate women and men; (b) to explore the characteristics of women and men who plan to major in computer science and how this population has evolved over time; and (c) to identify key determinants of the gender gap in computer science major aspirations during the past four decades.

Literature review

Despite a rich, several-decade history related to understanding the determinants of women's participation in STEM fields in the aggregate, only recently has discipline-specific, empirically based research begun to consider the reasons for women's disparate participation in particular STEM fields, such as computer science. This tradition within the literature is important given that research has shown that students pursuing a computer science undergraduate degree are quite distinct from other STEM students with respect to background characteristics, self-ratings, and career aspirations (Lehman, Sax, & Zimmerman, 2016). Thus, in the sections that follow, extant literature related to the gender gap in the computer science major choice is reviewed against the backdrop of what is known regarding determinants of the college STEM gender gap in general.

Personal inputs and background characteristics

A wealth of research has demonstrated that student background characteristics shape men and women's plans to pursue a STEM major. In general, the literature has suggested that lower-income, non-Asian racial/ethnic minorities, and first-generation college students are less likely to pursue STEM majors; among these groups, women are even less likely than their male counterparts to choose a STEM major (G. Huang, Taddese, & Walter, 2000; Seymour & Hewitt, 1997). Notably, the severity of the gender gap in STEM varies by racial/ethnic group, with the most pronounced gaps favoring men often occurring among Latino and African American students (Anderson & Kim, 2006; Smyth & McArdle, 2004).

Although few studies have examined the role of students' background characteristics in predicting plans to major in computer science, analyses of national enrollment and graduation data have revealed similar patterns in computer science degree attainment with respect to race (National Science Foundation [NSF], 2015; NCES, 2012). Although non-Asian racial/ethnic minorities are generally underrepresented in the STEM fields, Black students—both male and female—are better represented in computer science than they are among degree recipients across all fields.[1] Specifically, Black students constituted 16.7% of female and 8.6% of male bachelor's degree holders in computer science and only 10.9% of female and 7.7% of male degree recipients across all fields. Asian students were also overrepresented among computer science bachelor's degree recipients as they constituted 10.0% of female and 7.9% of male computer science graduates, relative to 6.2% of female and 7.0% of male college graduates across all fields. White women, by contrast, were less well-represented in computer science compared with their overall representation in higher education. In 2012, White women constituted 45.7% of female computer science graduates but earned 61.2% of all bachelor's degrees awarded to women. These statistics not only reveal differential representation of racial/ethnic groups among computer science graduates, but they also highlight that the magnitude of the gender gap in computer science varies by race and ethnicity.

Family influences and expectations

Previous studies have revealed a link between the role of family influences and expectations and students' decisions to pursue STEM majors in general and computer science specifically. Generally, families play a notable role as one of the earliest sources of influence on students' exposure to and interest in STEM subjects. They do so by serving as role models through their own careers, providing support or encouragement, and sending implicit and explicit messages regarding the acceptability or potential for their children to pursue STEM careers (H. S. Astin & Sax, 1996; Moakler & Kim, 2014).

Access to computing-related materials in the home is important for computing interest, with girls often exposed to computing later in life than boys (Margolis & Fisher, 2003). Relatedly, Margolis, Fisher, and Miller (2000) found that male computer science majors were more likely to report having owned their own computer or having had the family computer located in their room by an early age. Men also enter college with higher levels of confidence in their computing abilities compared with women; in fact, even men *not* intending to major in the field exhibit higher computing confidence than women who plan to major in computer science (Beyer, Rynes, Perrault, Hay, & Haller, 2003). Such gender gaps are critical given the well-documented connection between subject-area confidence and major selection in STEM (Fredricks & Eccles, 2002; Sax, Kanny, Riggers-Piehl, Whang, & Paulson, 2015).

K–12 experiences

Experiences within the K–12 environment (e.g., schools, teachers, pedagogy, curriculum, and classroom structure) also play an important role in predicting men and women's selection of a STEM major (P. M. Huang & Brainard, 2001; Kinzie, 2007). Research on STEM in the aggregate has revealed that increased exposure to STEM-related classroom activities, such as labs or simply being called upon by a teacher, positively predicts both male and female aspirations to major in a STEM field. However, girls tend to be excluded from these activities at greater rates than boys (Leedy, LaLonde, & Runk, 2003). Specific to computer science, research has shown that early computer experience in the classroom is a significant positive predictor of female students' interests in computer science (Margolis & Fisher, 2003; Tillberg & Cohoon, 2005). Hence, students' early classroom experiences, particularly their computing experiences, may inform their plans to pursue computing in college.

Students' precollege academic preparation and achievement are also key predictors of the decision to major in a STEM field, and particularly to major in computer science (Margolis, Fisher, & Miller, 2000; Seymour & Hewitt, 1997). Of concern is the persistent gender gap in Advanced Placement (AP) computer science courses—often considered a gateway to college-level computing majors; only 20% of computer science AP exam takers in 2014 were women (College Board, 2014).

Gender socialization, values, and perceptions

Differences in the way men and women are socialized and the impact on their subsequent value systems and perceptions contribute to their disparate participation in STEM fields (Eccles, 1987). In particular, women tend to perceive computer science as an individualistic field—one that does not emphasize societal impact—and are thus less likely to pursue computer science as a major (Weinberger, 2004; Wilson, 2002). Beyer, Rynes, and Haller (2004) argued that because women's values often do not align with those of the computer science field, "the average woman is unlikely to believe that she (a) could succeed in the major and (b) would derive much satisfaction from a career in computer science" (p. 26).

Women's awareness of STEM fields as being heavily male-dominated also negatively affects their participation in STEM (Blickenstaff, 2005; Carnevale, Smith, & Melton, 2011; Hill, Corbett, & St. Rose, 2010). Within computer science specifically, societal notions of computer science as a reclusive "hacker" field tend to discourage women from pursuing computing majors. The Geek Myth or the hacker image that is often associated with computer scientists can be more damaging for women's interest than it is for men's (Margolis & Fisher, 2003) and may deter women from entering the domain of computer science (Cheryan, Plaut, Davies, & Steele, 2009).

Women may also perceive STEM fields, particularly computing, to be overtly unwelcoming to women and may avoid pursuing a STEM major as a result (Han, Sax, & Kim, 2007; Williams & Ceci, 2012). Women who take computer science courses are less likely than men to view computing as a field that is compatible with raising a family (Beyer et al., 2004). Further, sexism within the technology sector may contribute to women's lack of interest in computer science. As has been well publicized in the media, a number of women have reported instances of sexism or sexual harassment within the tech industry (e.g., Carroll, 2014), which may dissuade others from pursuing or persisting in computer science (Lemons & Parzinger, 2007; Orser, Riding, & Stanley, 2012).

Conceptual framework

As evidenced by the literature, individual and environmental factors and their relationships with one another influence individuals' plans to pursue a certain career path. To conceptualize the present study, we drew from the body of literature on career development and utilized social cognitive career theory (SCCT) as a guiding framework (Lent, Brown, & Hackett, 1994).

SCCT describes the social cognitive process by which individuals develop interests and make career-related choices throughout their lifetime (see Figure 1). More specifically, the model of career-related choice behavior (MCRCB) posits that personal characteristics (e.g., race and gender), background contexts (e.g., parents' education), and learning experiences create opportunities for social feedback messages regarding what careers are possible and appropriate for certain individuals. These self-understandings result in one's perceived self-efficacy, outcome expectations, and interests regarding particular career options.

Of the social-cognitive variables, self-efficacy—a person's belief in his or her ability to succeed in a particular situation—has been shown to be the most central and pervasive mechanism of personal agency (Lent, Brown, & Hackett, 2002) and functions as an ever-evolving product of the interaction between a person's self-concept and the environment (Bandura, 1989). Outcome expectations—"personal beliefs about the consequences or outcomes of performing particular behaviors"—are also learned and molded through experiences (Lent et al., 2002, p. 262). Outcome expectations play a key role in motivating behavior and are directly influenced by learning experiences and self-efficacy. Self-efficacy and outcome expectations regarding activities have a direct effect on the formation of career interests and subsequent choice goals and actions (Lent et al., 2002).

Recognizing that interests develop early in childhood, SCCT describes how individuals cycle through exposure and reinforcement to pursue certain activities and achieve certain levels of performance. The more efficacious one feels in his or her ability and the more valuable the outcomes, the more enduring the interest will be. Furthermore, interests may exist around certain careers and

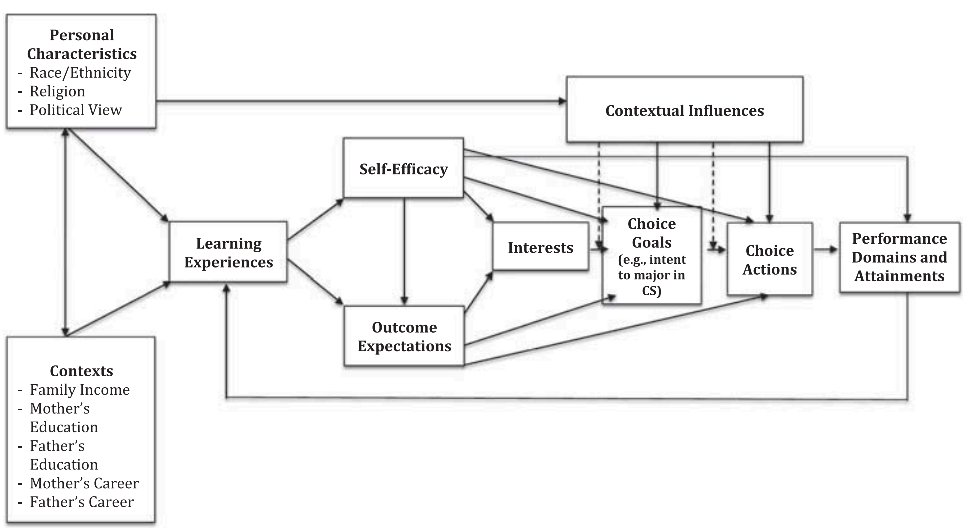

Figure 1. Model of Career-Related Choice Behavior (adapted from Lent et al., 1994).

professional fields, but self-efficacy, outcome expectations, and context will influence whether or not these interests are developed into goals. Contexts include environments such as local economies and job markets and physical access to developmental opportunities such as education and training.

Of relevance to this study are career choice goals. Within SCCT, career choice goals are described as "the determination to engage in a particular activity or to effect a particular future outcome" while choice actions are the action taken through consideration of goals and context (Lent et al., 2002, p. 263). Goals are an exercise of personal agency said to organize, guide, and sustain behavior without external reinforcement and for long periods of time. Choice goals describe the intent to engage while choice actions demonstrate the engagement in a specific activity or the act of affecting a particular outcome.

SCCT is a suitable framework for this study for several reasons. First, although numerous career development models exist (e.g., Eccles's [2004] expectancy value theory, Gottfredson's [1981] circumscription and compromise theory, and typology models such as Holland [1997], etc.), we determined that SCCT most closely fits the literature on STEM major selection as well as the variables we were interested in examining. SCCT also advances our desired conceptual approach in which we consider the person and his/her contexts as intertwined and in a relationship of influence over time. For example, as this study is particularly focused on the role of gender, SCCT is also appropriate as it positions gender (as well as other social identities) as an interwoven feature of a person's socially constructed world. SCCT emphasizes how gender evokes reactions from social-cultural environments and can relate to structures of opportunity within which career beliefs develop.

Second, Lent and colleagues suggested that the MCRCB is best applied to specific contexts, and empirical research has upheld the use of this model specifically within the context of STEM education (Byars-Winston, Estrada, Howard, Davis, & Zalapa, 2010; Lent, Lopez, Lopez, & Sheu, 2008; Soldner, Rowan-Kenyon, Inkelas, Garvey, & Robbins, 2012; Wang, 2013). Finally, this study contributes to one of the goals of SCCT, which is to bring together the constructs of self-concept and self-efficacy into a more universal framework. Research has long shown self-concept and self-efficacy to be empirically correlated (Bong & Clark, 1999; Lent, Brown, & Gore, 1997; Lent et al., 2002). In this study, we focused specifically on *math* self-concept as one form of self-efficacy, though we acknowledge that self-efficacy also refers to one's confidence to successfully apply their abilities to a given task (Bandura, 1997; Bong & Skaalvik, 2003).

Objectives

As highlighted in the previous sections, most research considers the factors contributing to the gender gap in STEM fields in the aggregate rather than within *specific* STEM fields, such as computer science. Further, research on the gender gap in STEM fields has generally not examined how the salience of various predictors of STEM major aspirations may have shifted across time. Because the characteristics of male and female college students have changed over the years (Sax, 2008) and perceptions of the STEM fields may have evolved as well, it is important to know whether individual STEM disciplines attract different types of women and men today than in the past. Accordingly, this study utilized national data on incoming college students collected during the past four decades to address the following research questions:

(1) How has the gender gap in incoming college students' intent to major in computer science changed during the past four decades?
(2) What are the determinants of women's and men's plans to major in computer science versus all other fields? To what extent have these determinants and/or their salience changed over time for women and men?
(3) To what extent is the gender gap in college students' plans to major in computer science due to: (a) gender differences in student attributes versus (b) gender differences in the salience of these attributes? How has this changed over time?

Methods

Data source and sample

This study utilized data from the Cooperative Institutional Research Program (CIRP) Freshman Survey, the oldest and largest longitudinal study of American higher education. The survey is administered to entering college students and covers a wide range of topics, including demographic background, high school experiences, college expectations, self-concepts, values, and life goals as well as the students' academic and career aspirations. The CIRP Freshman Survey uniquely enabled this study to explore the changing trends in students' interest to major in computer science across four decades and link this key variable to a common set of independent variables from 1971 to 2011. Other national data sets do not go back as far as this survey does and/or follow only one cohort of students for an extended period of time (e.g., National Education Longitudinal Study of 1988 [NELS:88], National Longitudinal Study of 1972 [NLS-72]).

This study was based on CIRP data from 1,225 baccalaureate-granting institutions from 1971 to 2011. The trend analysis explored how the intent to major in computer science has varied by gender from 1971 to 2011 and was based on an unweighted sample of 8,038,061 respondents across the four decades (3,662,692 men and 4,375,369 women). The sample for the descriptive trend analysis was then weighted by student gender and institutional control, type, and selectivity so that it would reflect the population of first-time, full-time college students at all 4-year institutions in the United States for each year. (See Pryor, Hurtado, Saenz, Santos, & Korn, 2007, for information on the weighting scheme, validity, and reliability.)

The regression analyses provided insight into the predictive power of key variables (described in the next section on measures) in men's and women's computer science major plans and focused on five specific years of survey data: 1976, 1986, 1996, 2006, and 2011. These years were selected because they contained the most consistent set of survey items at evenly spaced decade (and half-decade) intervals. The unweighted regression sample from across these 5 years was composed of 18,830 students intending to major in computer science (4,127 women and 14,703 men) and 904,307 students (495,397 women and 408,910 men) from all other majors.

Measures

Men's and women's self-reported plans to major in computer science (vs. all other majors) served as the dependent variable in this study. Given that this study was focused on how the determinants of aspiring to a computer science major have shifted over the years, time served as a key independent variable in this study. Time was operationalized as a continuous year variable.

Additional independent variables were selected in line with Lent et al.'s (1994) MCRCB. They were placed into temporally sequenced blocks to best understand predictors of enrollment into computer science. A series of correlations and factor analyses were conducted to narrow the list of variables to those that were most conceptually and statistically interesting in understanding how students make plans about their college major. Only variables that were collected across each of the 5 years (1976, 1986, 1996, 2006, 2011) were included in this analysis. Drawn from the CIRP Freshman Survey, the final set of 41 variables was categorized into eight blocks.

The blocks reflected constructs from the MCRCB to the extent possible by the variables available in the data set.[2] These blocks included: *personal characteristics, background contexts, learning experiences, self-efficacy, outcome expectations, interests, contextual influences*, and *choice goals*. *Personal characteristics* and *background contexts* included variables that likely influence the development of career ideas during one's life span. High school grade point average fit under *learning experiences* as it represents the culmination of academic performance. *Self-efficacy* was most closely represented by math self-concept because a measure of computing self-efficacy was not available. *Outcome expectations* variables represent indicators of expected success or persistence in their major field. *Interest* variables represent various goals and orientations that may encourage or discourage pursuit of a specific academic path. *Contextual influences* (e.g., financial concerns, distance from home, institutional type) impact the perceived availability of major choices or programs and/or reflect environments that could influence the need for some individuals to select future careers or majors based on their current economic situation or other external needs. Under *choice goals*, degree type and career aspiration goals represent broad motivators that could influence individuals to select certain STEM or non-STEM majors. The dependent variable—intent to major in computer science—is also a career-related goal but is separate from the other goals because it is more proximal to the choice action of actually declaring a computer science major. The complete list of independent variables used for the regression analysis, along with their coding schemes, is provided in Appendix A.

Factor analysis procedures

The research team conducted factor analysis using principal axis factoring with Promax rotation to determine what factors would be used for the regression analysis. Previously constructed factors from A. W. Astin's (1993) model of student types as well as Sax's (2008) typology and college choice factors guided factor analysis. Of the 65 independent variables considered, seven factors were created. (See Appendix B for a list of factors, their loadings, and reliability.) The threshold for reliability was set at a Cronbach's *alpha* of .65,[3] and variables were only considered valid for inclusion in a factor if they loaded at .40 or higher (ultimately, all loadings exceeded .60).

Data analysis

Research Question 1 examined how the gender gap in incoming students' intent to major in computer science has changed since 1971. To address this question, the 40-year trends were used to compare the proportions of men and women who reported plans to major in computer science on the CIRP Freshman Survey. We also reported long-term trends in the fraction of all computer science majors who were women.

Research Question 2 examined the determinants of intending to major in computer science and explored if these determinants and/or their predictive power have changed over time. To answer this research question, logistic regression analyses were conducted separately by gender across the 5-year data set (i.e., 1976, 1986, 1996, 2006, and 2011) to predict the likelihood of incoming college students planning to pursue computer science as their major (vs. all other majors). First, the model was run with all 41 variables to determine which variables were statistically significant ($p < .001$). Those variables that were not significant for either gender were removed from the model. Then, the logistic regressions were rerun with the remaining variables, using identical models for women and men. Finally, Year × Variable interaction terms were added to identify if and how the salience of each variable changed over time for each gender.

Research Question 3 examined the extent to which the gender gap in computer science major aspirations is due to gender differences in the attributes of undergraduate women and men versus gender differences in the *salience* of these attributes and how this has changed over time. To answer this research question, we employed the regression-based decomposition technique designed for nonlinear models (Fairlie, 2005). Decomposition analysis uses regression and mean replacement to better understand how populations change over time and has been used in research on gender and STEM careers (Xie & Shauman, 2003). This study utilized the Blinder-Oaxaca decomposition technique, a well-known method used to identify the unique contributions of group differences to observed outcome gaps (e.g., those based on gender or race; Blinder, 1973; Fairlie, 2005; Oaxaca, 1973). More specifically, the technique decomposed the group difference in an outcome into: (a) the part attributable to differences in average characteristics between the groups and (b) the part attributable to the group differences in the salience (coefficient) of the characteristics (as well as residual errors in the model due to bias from omitted variables). Respectively, these decompositions are often called the "explained" and "unexplained" portions of the gap.

The standard Blinder-Oaxaca decomposition cannot be directly used when the outcome measure is binary, such as selection of a computer science major (Fairlie, 2005). Therefore, we turned to the nonlinear extension of the Blinder-Oaxaca decomposition written by Fairlie (2005), which can handle decomposition for binary outcomes, especially when the outcome is extreme (i.e., not located near the middle of distribution). Further, although decomposition can be performed from the "perspective" of one group or another (e.g., choosing either male or female as a base group), this study followed the suggestion by Oaxaca and Ransom (1994) and used coefficient estimates from a pooled sample of the two gender groups.

Results

Trends over time

Results from Research Question 1 revealed clear trends in men's and women's intent to major in computer science from 1971 to 2011 (see Figure 2). Across all years, men were more likely than women to major in computer science, though interest in this field fluctuated over time for both genders. Intent to major in computer science grew substantially from the field's nascency in the early 1970s (when it attracted only 0.85% of women and 1.3% of men in 1971) and spiked for both genders in the early 1980s (reaching 6.7% of women in 1982 and 9.4% of men in 1983). However, interest in computer science quickly diminished during the next decade as it declined to 1.5% of women and 3.3% of men by 1990. Renewed interest in computer science was again evident in the mid-to-late 1990s (during the dot-com boom); however, this resurgence occurred almost exclusively for

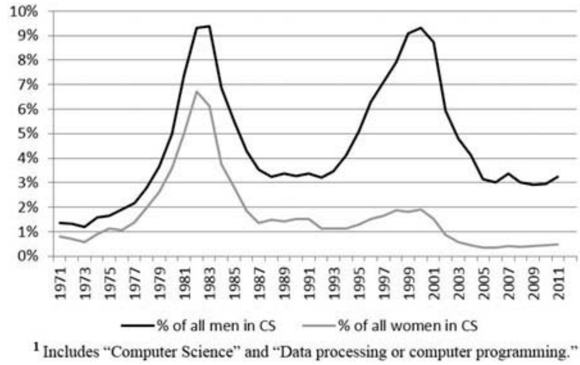

Figure 2. Proportion of entering students who plan to major in computer science (CS), by gender (1971–2011).

male students: In 2000, men's interest peaked at 9.3%, whereas women's only reached 1.9%. Declines during the next decade show that by 2011, only 3.3% of men and 0.4% of women planned to major in computer science. Overall, these trends revealed tremendous fluctuation in interest in computer science majors and further indicated that the gender gap favoring men became especially evident during the computing field's significant expansion in the 1990s.[4]

Another way to consider the gender gap is to examine trends in the total fraction of computer science majors who are women. As shown in Figure 3, the proportion of women who are computer science majors has been on a downward trajectory for most of the past four decades. The representation of women reached its peak of 44% in 1980, just as the field was beginning to gain traction. Women's share of computer science majors quickly dropped in the early 1980s and has been on a nearly constant decline since then. By the mid-2000s, the number of women who were computer science majors had dropped to 12%, and this number rebounded only slightly to 15% by 2011.[5]

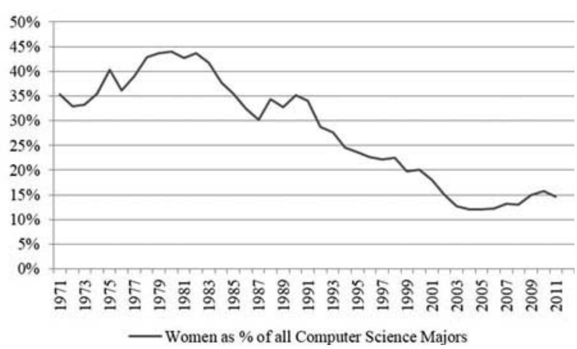

Figure 3. Proportion of entering prospective computer science majors who are female (1970–2011).

Logistic regression results

Research Question 2 examined which student characteristics predict men's and women's intent to major in computer science and tested whether the salience of these predictors has changed over time. Of the 41 variables included in the initial regression, 38 emerged as significant ($p < .001$) for either women or men; these 38 variables were included in the final logistic regression models run separately by gender.

Tables 1 and 2 display results for women and men in terms of two models: Model 1, which represents the main effects of independent variables across all years, and Model 2, which reflects the main effects of independent variables in the base year 1976, along with interaction terms to indicate shifts over time in the predictive power of independent variables. To clarify the interpretation of interaction terms, a significant positive interaction term denotes a positive effect that has grown stronger with time *or* a negative effect that has weakened over time. Conversely, a significant negative interaction term indicates a positive effect that has grown weaker over time *or* a negative effect that has strengthened with time. Thus, interaction terms must be interpreted alongside their main effects.

Because this study was concerned primarily with examining change over time in women's and men's computer science interests, results are organized into four major categories: (a) predictors that have remained stable over time for both genders, (b) predictors that have changed in salience for both genders, (c) predictors that have changed in salience only for women, and (d) predictors that have changed in salience only for men.

Predictors remaining stable over time for both genders

Across the time frame examined, several student characteristics emerged as consistent predictors of men's and women's intent to major in computer science. Among these predictors, we found that students whose fathers had a career in STEM and those who placed greater value on status or wealth were more likely to plan to major in computer science. In addition, for both genders, an orientation toward social activism was a negative predictor of interest in computer science across all time periods. Further, women and men who attended research universities or who aspired to earn master's, law, or medical degrees were consistently less likely to plan to major in computer science. The results also indicated that Asian/Pacific Islander and African American students have been consistently more likely to intend to major in computer science than their White peers. This finding aligns with national degree attainment data, as presented earlier.

Some variables indicated a relationship that was stable over time but only *significant* for one gender or another. For example, male intended computer science majors were consistently more likely than other majors to report

Table 1. Logistic regression predicting intent to major in computer science (compared to all other majors) among women across years (n = 499,524).

	Model 1			Model 2		
Variables	b	SE	Ex(B)	b	SE	Exp(B)
Year (continuous)	−0.311	0.015	0.733	0.877	0.161	2.404
Personal characteristics						
Religion (vs. Protestant)						
Catholic	0.032	0.041	1.033	0.050	0.090	1.052
Jewish	0.123	0.108	1.131	−0.476	0.232	0.621
Other	**0.464**	0.050	**1.591**	0.345	0.125	1.413
No religion	0.147	0.051	1.158	0.035	0.122	1.036
Race (vs. White)						
Other/Multi	**0.394**	0.073	**1.483**	0.501	0.200	1.650
Asian/Pacific Islander	**0.758**	0.062	**2.133**	**0.907**	0.160	**2.478**
Black	**1.267**	0.060	**3.551**	**1.139**	0.136	**3.123**
Latino/a	**0.694**	0.086	**2.002**	**1.391**	0.223	**4.018**
Political views	0.021	0.023	1.021	0.076	0.054	1.079
Background contexts						
Mother's education	**−0.051**	0.010	**0.951**	**−0.076**	0.022	**0.927**
Family income	**−0.107**	0.014	**0.898**	**−0.222**	0.031	**0.801**
Father's career: STEM	**0.342**	0.041	**1.407**	0.136	0.095	1.145
Learning experiences						
High school GPA	−0.006	0.013	0.994	**0.116**	0.030	**1.123**
Self-efficacy						
Self-rating: math ability	**0.747**	0.020	**2.111**	**1.092**	0.046	**2.979**
Leader (factor)	**−0.248**	0.020	**0.781**	−0.029	0.046	0.971
Scholar (factor)	0.041	0.023	1.041	**−0.236**	0.051	**0.789**
Outcome expectations						
Future act: change major field	0.058	0.018	1.060	0.120	0.039	1.128
Future act: make at least a 'B' avg.	0.051	0.030	1.052	0.176	0.067	1.192
Interests						
Goal: meaningful philosophy	−0.029	0.019	0.971	−0.093	0.042	0.911
Goal: theoretical scientific contrib.	**0.303**	0.020	**1.354**	0.141	0.046	1.152
Goal: raising a family	**−0.091**	0.017	**0.913**	0.104	0.038	1.110
Social activist (factor)	**−0.331**	0.023	**0.718**	**−0.189**	0.052	**0.827**
Artistic (factor)	**−0.160**	0.020	**0.852**	**−0.393**	0.047	**0.675**
Status striver (factor)	**0.192**	0.019	**1.212**	**0.154**	0.044	**1.166**
Educational reasons for college (factor)	**−0.097**	0.018	**0.908**	**−0.158**	0.040	**0.854**
Extrinsic reasons for college (factor)	**0.229**	0.021	**1.258**	**0.305**	0.046	**1.356**
Contextual influences proximal to choice behavior						
Distance of institution from home	−0.030	0.013	0.970	−0.001	0.029	0.999
Number of institutions applied to	−0.010	0.008	0.990	0.046	0.021	1.047
Student-to-faculty ratio	0.007	0.004	1.008	0.020	0.011	1.020
Institutional type: university	**−0.277**	0.041	**0.758**	**−0.451**	0.090	**0.637**
Institutional type: religious	**−0.247**	0.059	**0.781**	−0.032	0.136	0.969
Institutional Type: HBCU	0.194	0.085	1.214	0.115	0.189	1.122
Institutional control: public	0.036	0.053	1.036	**0.493**	0.125	**1.637**
Choice goals						
Degree aspirations (vs. BA)						
PhD	**−0.837**	0.055	**0.433**	**−0.723**	0.131	**0.485**
Law degree	**−1.699**	0.155	**0.183**	**−2.311**	0.383	**0.099**
Medical degree	**−3.093**	0.149	**0.045**	**−3.189**	0.369	**0.041**
Master's degree/MDiv	**−0.242**	0.036	**0.785**	−0.260	0.079	0.771
Interaction terms						
Catholic × Time				−0.019	0.033	0.981
Jewish × Time				0.233	0.078	1.263
Other × Time				0.038	0.047	1.039

(*Continued*)

Table 1. (Continued).

Variables	Model 1 b	Model 1 SE	Model 1 Ex(B)	Model 2 b	Model 2 SE	Model 2 Exp(B)
No Religion × Time				0.033	0.038	1.033
Other/Multi × Time				−0.038	0.057	0.963
Asian/Pacific Islander × Time				−0.044	0.049	0.957
Black × Time				0.049	0.046	1.050
Latino/a × Time				−0.194	0.068	0.824
Political Views × Time				−0.025	0.018	0.975
Mother's Education × Time				0.008	0.007	1.009
Family Income × Time				**0.045**	0.011	**1.046**
Father's Career: STEM × Time				0.074	0.031	1.077
High School GPA × Time				**−0.050**	0.011	**0.951**
Self-Rating: Math Ability × Time				**−0.131**	0.015	**0.877**
Leader (factor) × Time				**−0.079**	0.015	**0.924**
Scholar (factor) × Time				**0.100**	0.017	**1.105**
Future Act: Change Major Field × Time				−0.023	0.014	0.977
Future Act: Make "B" Average × Time				−0.048	0.023	0.953
Goal: Meaningful Philosophy × Time				0.022	0.014	1.023
Goal: Theoretical Scientific Contribution × Time				**0.060**	0.015	**1.062**
Goal: Raising a Family × Time				**−0.073**	0.013	**0.929**
Social Activist (factor) × Time				−0.054	0.017	0.948
Artistic (factor) × Time				**0.083**	0.015	**1.086**
Status Striver (factor) × Time				0.017	0.015	1.017
Educational Reasons for College (factor) × Time				0.025	0.014	1.025
Extrinsic Reasons for College (factor) × Time				−0.030	0.016	0.971
Distance of Institution From Home × Time				−0.014	0.010	0.986
Number of Institutions Applied To × Time				−0.017	0.006	0.983
Student-to-Faculty Ratio × Time				−0.004	0.004	0.996
Institutional Type: University × Time				0.071	0.033	1.074
Institutional Type: Religious × Time				−0.071	0.046	0.931
Institutional Type: HBCU × Time				0.060	0.063	1.062
Institutional Control: Public × Time				**−0.169**	0.042	**0.845**
PhD × Time				−0.029	0.043	0.972
Law × Time				0.227	0.119	1.255
Medical Degree × Time				0.044	0.116	1.045
Master's Degree/MDiv × Time				0.017	0.028	1.017

Note. Bold indicates $p < .001$. STEM = science, technology, engineering, and math; GPA = grade point average; HBCU = Historically Black Colleges and Universities.

more liberal political views, to expect that they will earn at least a "B" average in college, and to attend college closer to home. Further, they were less likely than men in other majors to identify as Catholic and more likely to indicate no religious preference. None of these variables were significant for women at any time point; the one stable predictor for women (that has no predictive power for men) was attending college for educational reasons, which consistently predicted women's plans *not* to major in computer science.

Predictors changing in salience for both genders

More than half of the variables predicting computer science major intentions revealed effects that have become more or less salient over time, with some

Table 2. Logistic regression predicting intent to major in computer science (compared to all other majors) among men across years (n = 423,613).

	Model 1			Model 2		
Variables	b	SE	Ex(B)	b	SE	Ex(B)
Year (continuous)	0.029	0.007	1.030	0.640	0.080	1.896
Personal characteristics						
Religion (vs. Protestant)						
Catholic	**−0.128**	0.023	**0.880**	−0.117	0.056	0.889
Jewish	0.095	0.052	1.100	−0.080	0.123	0.923
Other	**0.258**	0.032	**1.294**	0.245	0.082	1.277
No religion	**0.097**	0.024	**1.102**	0.090	0.065	1.095
Race (vs. White)						
Other/Multi	0.092	0.037	1.097	**0.530**	0.111	**1.699**
Asian/Pacific Islander	**0.243**	0.035	**1.276**	**0.468**	0.105	**1.596**
Black	**0.458**	0.044	**1.580**	**0.766**	0.112	**2.151**
Latino/a	0.025	0.051	1.025	**0.882**	0.155	**2.415**
Political views	**0.051**	0.011	**1.052**	−0.018	0.029	0.982
Background contexts						
Mother's education	0.010	0.005	1.010	**0.052**	0.013	**1.054**
Family income	**−0.131**	0.007	**0.877**	**−0.190**	0.018	**0.827**
Father's career: STEM	**0.239**	0.022	**1.270**	0.147	0.057	1.158
Learning experiences						
High school GPA	**−0.036**	0.007	**.965**	0.016	0.017	1.016
Self-efficacy						
Self-rating: math ability	**0.344**	0.011	**1.410**	**0.480**	0.029	**1.616**
Leader (factor)	**−0.369**	0.010	**0.691**	**−0.190**	0.027	**0.827**
Scholar (factor)	**0.141**	0.012	**1.151**	−0.006	0.031	0.994
Outcome expectations						
Future act: change major field	**−0.220**	0.010	**0.803**	**−0.124**	0.026	**0.883**
Future act: make at least a 'B' avg.	**0.075**	0.016	**1.078**	**0.154**	0.042	**1.167**
Interests						
Goal: meaningful philosophy	**−0.050**	0.010	**0.951**	**−0.202**	**0.026**	**0.817**
Goal: theoretical scientific contribution	**0.368**	0.010	**1.445**	**0.336**	0.027	**1.399**
Goal: raising a family	**−0.043**	0.010	**0.958**	**0.107**	0.025	**1.113**
Social activist (factor)	**−0.355**	0.012	**0.701**	**−0.327**	0.031	**0.721**
Artistic (factor)	**−0.049**	0.010	**0.952**	−0.025	0.028	0.976
Status striver (factor)	**0.087**	0.011	**1.091**	0.018	0.028	1.018
Educational reasons for College (factor)	0.008	0.009	1.009	−0.010	0.023	0.990
Extrinsic reasons for College (factor)	**0.138**	0.011	**1.148**	**0.275**	0.027	**1.316**
Contextual influences proximal to choice behavior						
Distance of institution from home	**−0.055**	0.007	**0.946**	−0.057	0.018	0.945
Number of institutions applied to	**−0.022**	0.004	**0.978**	**0.058**	0.012	**1.060**
Student-to-faculty ratio	**0.017**	0.002	**1.017**	**0.026**	0.006	**1.027**
Institutional type: university	**−0.323**	0.022	**0.724**	**−0.345**	0.055	**0.708**
Institutional type: religious	**−0.239**	0.032	**0.788**	0.090	0.083	1.094
Institutional type: HBCU	−0.024	0.069	0.976	0.010	0.167	1.010
Institutional control: public	**−0.100**	0.028	**0.905**	0.207	0.071	1.229
Choice goals						
Degree aspirations (vs. BA)						
PhD	**−0.593**	0.028	**0.553**	**−0.280**	0.071	**0.756**
Law degree	**−1.825**	0.094	**0.161**	**−2.022**	0.223	**0.132**
Medical degree	**−2.816**	0.082	**0.060**	**−2.735**	0.198	**0.065**
Master's degree/MDiv	**−0.194**	0.020	**0.823**	−0.072	0.051	0.930
Interaction terms						
Catholic × Time				−0.009	0.017	0.991
Jewish × Time				0.048	0.038	1.049
Other × Time				−0.007	0.026	0.993

(*Continued*)

Table 2. (Continued).

Variables	Model 1 b	Model 1 SE	Model 1 Ex(B)	Model 2 b	Model 2 SE	Model 2 Ex(B)
No Religion × Time				−0.007	0.018	0.993
Other/Multi × Time				**−0.123**	0.030	**0.884**
Asian/Pacific Islander × Time				−0.065	0.029	0.937
Black × Time				−0.099	0.033	0.906
Latino/a × Time				**−0.234**	0.042	**0.791**
Political Views × Time				0.023	0.009	1.023
Mother's Education × Time				**−0.015**	0.004	**0.985**
Family Income × Time				**0.021**	0.006	**1.021**
Father's Career: STEM × Time				0.029	0.017	1.030
High School GPA × Time				**−0.018**	0.005	**0.982**
Self-Rating: Math Ability × Time				**−0.042**	0.008	**0.959**
Leader (factor) × Time				**−0.056**	0.008	**0.946**
Scholar (factor) × Time				**0.043**	0.009	**1.044**
Future Act: Change Major Field × Time				**−0.031**	0.008	**0.969**
Future Act: Make "B" Average × Time				−0.023	0.012	0.977
Goal: Meaningful Philosophy × Time				**0.050**	0.008	**1.051**
Goal: Theoretical Scientific Contribution × Time				0.010	0.008	1.010
Goal: Raising a family × Time				**−0.050**	0.007	**0.952**
Social Activist (factor) × Time				−0.007	0.009	0.993
Artistic (factor) × Time				−0.010	0.008	0.990
Status Striver (factor) × Time				0.022	0.008	1.022
Educational Reasons for College (factor) × Time				0.006	0.007	1.006
Extrinsic Reasons for College (factor) × Time				**−0.045**	0.008	**0.956**
Distance of Institution From Home × Time				−0.002	0.005	0.998
Number of Institutions Applied to × Time				**−0.022**	0.003	**0.978**
Student-to-Faculty Ratio × Time				−0.003	0.002	0.997
Institutional Type: University × Time				0.015	0.017	1.015
Institutional Type: Religious × Time				**−0.104**	0.025	**0.902**
Institutional Type: HBCU × Time				−0.006	0.049	0.994
Institutional Control: Public × Time				**−0.096**	0.021	**0.908**
PhD × Time				**−0.100**	0.021	**0.904**
Law × Time				0.068	0.067	1.070
Medical Degree × Time				−0.026	0.060	0.975
Master's Degree/MDiv × Time				−0.041	0.015	0.960

Note. Bold indicates $p < .001$. STEM = science, technology, engineering, and math; GPA = grade point average; HBCU = Historically Black Colleges and Universities.

indicating shifts for both genders. For example, interaction terms revealed that having a scholarly orientation (i.e., a high degree of academic and intellectual self-confidence) was increasingly predictive of computer science major aspirations for both women and men. Further, men and women with orientations toward leadership or toward raising a family were increasingly disinclined to intend to major in computer science.

However, two noteworthy predictors actually weakened in salience over time: students' mathematical self-concept and family income. While mathematical self-rating continued to be a significant positive predictor of planning to major in computer science, its predictive power became significantly weaker over time. Family income was negatively associated with the intent to major in computer science for both women and men, but this relationship diminished in strength for both genders.

The predictive power of high school academic achievement also changed in salience for both genders but in slightly different ways. For men, the negative predictive power of high school grades became stronger over time, suggesting that computer science has attracted increasingly lower-achieving men. For women, though main effects of high school grades across all years were not significant, Model 2 revealed that high school grades positively predicted the selection of computer science in 1976 (base year), but that relationship became weaker over time.

Predictors changing in salience only for women

Two variables evidenced a changing salience that was observed only for women. First, the variable of having a scientific orientation became an even stronger positive predictor among women. In other words, having a commitment to scientific inquiry is now more strongly associated with women's intent to major in computer science than it was in prior decades. On the other hand, one variable that consistently detracted from interest in computer science—students' artistic orientation—became a weaker predictor among women. This latter finding revealed that women who view themselves as creative and artistic are now less likely to be deterred from computer science.

Predictors changing in salience only for men

Several variables revealed a strengthening or weakening in predictive power only for men. Among them, we found that men were increasingly *less* likely to select computer science as their probable major if they applied to a greater number of colleges, or aspired to earn a Ph.D. Men who expected to change their major field were also increasingly less likely to plan to major in computer science, suggesting that with time, male computer science majors have become *more* committed to their choice of major. Male intended computer science majors were also increasingly less likely to be found at public or religiously affiliated institutions.

Some variables became less salient over time for men only. Specifically, computer science historically attracted men who were less interested in developing a meaningful philosophy of life and more interested in college for its extrinsic benefits (i.e., better job and more money). However, these longstanding relationships became significantly weaker over time, suggesting that men with more philosophical and less pecuniary orientations became less likely to be deterred from majoring in computer science.

Regression decomposition results

Whereas Research Question 2 focused on the predictors of computer science major intentions for women and men, Research Question 3 focused on the determinants of the gender gap itself. During the years used in the multivariate analysis (1976, 1986, 1996, 2006, and 2011), the gender gap among computer science majors (i.e., the difference in the percentage of students from each gender selecting this major) fluctuated from a low of 1% in 1976 to a high of 5% in 1996. For each year, Table 3 shows the proportion of the gap that is attributable to differences in the mean *observable characteristics* of women and men who identified computer science as their probable major (explained portion) versus gender differences in the *salience* of the variables that predicted computer science major plans (unexplained portion).[6] For example, in 1976, the explained portion was 78.7% and the unexplained portion was 21.3%. In other words, approximately 79% of the gender gap in the intent to major in computer science could be explained by the fact that men and women differed in observable measures such as self-rated mathematical ability and SAT math scores. The rest of the gender gap (approximately 21%) could be considered attributable to gender differences in the extent to which the observable measures predicted computer science major plans.

In the years subsequent to 1976, the gender gap became primarily attributable to gender differences in the predictive power of student characteristics. Specifically, in 1986, 1996, 2006, and 2011, the unexplained portion of the gender gap (approximately 56%–65%) in computer science major intentions remained because women and men differed in the salience of the variables that predicted computer science major plans. In other words, even if women and men had equivalent scores on key predictors of intending to major in computer science (e.g., self-rated math ability), more than half of the gender gap would remain.

Table 4 provides additional detail on this explained portion by showing the proportion of the overall gap that is due to gender differences in specific student characteristics. In other words, these percentages are estimates of the portion of the overall gender gap that would have been eliminated if men and women were (on average) the same in given characteristics. Most of the time, the percentage is indicated as a

Table 3. Decomposition of gender gap in intent to major in computer science.

	1976 (%)	1986 (%)	1996 (%)	2006 (%)	2011 (%)
Explained	78.7	44.0	39.1	35.5	34.9
Unexplained	21.3	56.0	60.9	64.5	65.1
Total gap	100.0	100.0	100.0	100.0	100.0

Table 4. Detailed regression decomposition of intent to major in computer science, by year.

	1976 (*N* = 168,787)	1986 (*N* = 151,474)	1996 (N = 201,665)	2006 (*N* = 237,334)	2011 (*N* = 170,096)
Total difference	.008	.024	.047	.025	.025
Unexplained	.002	.014	.028	.016	.017
Explained	.006	.011	.018	.009	.009
Personal characteristics					
Religion (vs. Protestant)	% of total	% of total	% of total	% of total	% of total
Catholic	−0.20	−0.01	0.17	0.06	0.16
Jewish	−0.01	−0.01	0.18	−0.01	0.04
Other	0.05	**−1.41**	0.09	−0.03	−0.06
No religion	−0.66	0.90	**0.57**	0.67	**1.06**
Race (vs. White)					
Other/Multi	0.08	0.05	−0.08	−0.02	−0.03
Asian/Pacific Islander	0.14	0.62	**0.52**	0.00	−0.06
Black	**−10.80**	**−5.47**	**−1.18**	−1.07	−0.82
Latino/a	0.21	−0.06	−0.08	−0.05	0.00
Political Views	−0.28	−0.44	0.38	−0.17	−0.37
Background contexts					
Mother's education	−0.30	−0.56	−0.04	0.35	0.21
Family income	−3.97	**−2.59**	**−0.90**	**−1.79**	−0.61
Father's career: STEM	0.24	0.57	0.23	0.35	0.25
Learning experiences					
High school GPA	−1.20	**1.86**	**3.00**	**3.24**	**1.56**
Self-efficacy					
Self-rating: math ability	**78.64**	**32.00**	**14.43**	**13.13**	**13.12**
Leader (factor)	−4.00	**−5.08**	**−2.39**	0.55	−1.26
Scholar (factor)	−4.46	1.47	**3.97**	**2.41**	**4.73**
Outcome Expectations					
Future act: change major field	0.01	**0.70**	**0.43**	−0.12	−0.20
Future act: make at least a "B" average	0.11	0.31	0.08	−0.02	−0.01
Interests					
Goal: meaningful philosophy	0.64	0.10	−0.02	−0.12	−0.02
Goal: theoretical scientific contribution	**12.01**	**14.88**	**6.38**	**4.44**	**5.21**
Goal: raising a family	−0.10	0.16	−0.04	**0.60**	0.16
Social activist (factor)	**6.62**	**6.85**	**9.54**	**8.53**	**8.56**
Artistic (factor)	**8.61**	**1.35**	0.14	**1.37**	1.29
Status striver (factor)	0.19	0.99	**2.67**	0.35	0.57
Educational reasons for college (factor)	**8.71**	**2.67**	**1.85**	**1.92**	1.03
Extrinsic reasons for college (factor)	**5.33**	**1.31**	**0.77**	**0.41**	0.21
Contextual influences proximal to choice behavior					
Distance of institution from home	−0.15	**−1.22**	**−0.41**	−0.42	−0.22
Number of institutions applied to	1.41	−0.35	−0.04	0.21	0.31
Student-to-faculty ratio	0.33	−0.17	−0.03	0.03	0.02
Institutional type: university	−1.79	**−2.33**	**−0.84**	−1.04	−1.21
Institutional type: religious	2.71	0.32	0.38	**1.74**	**2.48**

(*Continued*)

Table 4. (Continued).

	1976 (N = 168,787)	1986 (N = 151,474)	1996 (N = 201,665)	2006 (N = 237,334)	2011 (N = 170,096)
Institutional type: HBCU	−2.26	−0.14	−0.14	0.09	−0.18
Institutional control: public	1.65	0.26	−0.20	−0.83	−0.93
Choice goals					
Degree aspirations (vs. BA)					
PhD	**−5.72**	**−2.23**	−0.67	−0.17	−1.05
Law degree	**−5.14**	0.41	0.01	−0.02	−0.10
Medical degree	**−7.48**	**−1.28**	0.19	0.98	0.78
Master's and MDiv degree	−0.43	−0.43	0.20	−0.07	0.26

Note. Bold indicates $p < .001$. STEM = science, technology, engineering, and math; GPA = grade point average; HBCU = Historically Black Colleges and Universities.

positive number (i.e., the gender gap in plans to pursue the computer science major is attributable in part to men's and women's differing means on a particular variable). However, occasionally, the percentage is negative, which indicates that the gender gap in computer science would have been even larger if not for gender differences in the characteristic.[7]

Over time, three variables stood out as the most prominent explanations for the gender gap in computer science (i.e., those that account for at least 5% of the overall gap). The first, and by far the most important, variable was students' self-rated math ability. Women's tendency to rate themselves lower than men on their mathematical skills was the primary explanation for the gender gap in computer science, though its salience has weakened over time; in 1976, gender differences in math self-rating accounted for 78.6% of the computer science gender gap, whereas by 2011, it explained only 13.1% of the computer science gender gap (though it remained the top explanatory variable).

The second key variable from the decomposition analysis was students' commitment to making "a theoretical contribution to science." Women tended to place less value on this goal than did men, a difference that accounted for 4.4% to 14.9% of the gender gap in students' computer science major intentions.

The third prominent explanation for the gender gap in computer science major aspirations was students' commitment to social activism. The fact that women placed greater value on social activism (i.e., helping others in difficulty and influencing social values) explained 6.6% to 9.5% of the gender gap in computer science. Many other variables in Table 4 were considered statistically significant determinants of the gender gap in computer science, but they either represented only a very small portion of the explanation or their salience diminished over time.

Limitations

This study builds on previous research and contributes to the knowledge base about the gender gap in computer science and how this gap has changed over time. However, we acknowledge some important limitations. First, the sample for this study included only first-time, full-time students entering 4-year colleges and universities and thus excluded community college students. This is an important area for future research given that community colleges enroll a higher proportion of nontraditional students (e.g., older, low-income, female, racial/ethnic-minority) than do 4-year institutions, and the community college is a key pathway for women and underrepresented students pursuing STEM education (Berger & Malaney, 2003; Mooney & Foley, 2011; Starobin & Laanan, 2005).

Additionally, the dependent variable only considered students' intention to major in computer science upon entry to college. On the survey instrument, incoming college students were asked to identify their "probable field of study" and could indicate only one major field. However, we do not know if the intended computer science majors in our sample ultimately majored in that field or continued on to complete a computer science degree. For the purposes of this study, we included students who planned to major in either "computer science" or "data processing or computer programming" to be inclusive of all students intending to major in a computing field. However, we acknowledge that there may be distinct differences between the types of students who selected these choices. Additionally, in the early years of our study's time frame, some students who planned to study computer science may have identified under another major, such as mathematics, and therefore may not be fully represented.[8]

The use of five distinct time points (i.e., 1976, 1986, 1996, 2006, and 2011) also presented challenges. First, because we limited our variables to those survey items that were available for all five time points, we were not able to include all variables thought to be important to computer science major selection (e.g., gender-role socialization, math and science coursework in high school). Second, our study may have failed to capture fluctuations in the gender gap in the years in between our chosen time points. Additionally, the time variable was coded such that we were unable to capture nonlinear changes in salience of relevant variables (i.e., some variables could have increased or decreased at an uneven pace). Finally, the most recent time point available for the variables used in this study was 2011; more recent data regarding degree completion indicates that computer science has increased in popularity since 2011 (NCES, 2014). Hence, future research should continue to consider the most recent data available to capture these emerging trends.

Finally, there were some important limitations to our use of SCCT as it applied to the data for this study. First, self-efficacy figures prominently in

SCCT, and Bandura (2006) argued that self-efficacy is most reliable as a predictor when it captures beliefs about performance within a specific domain. Though a measure of self-efficacy related to performance in the field of computer science would have been ideal for this study, one was not available for all years. However, previous research has shown that math self-concept is an important predictor of students' plans to major in computer science and was therefore included instead (Sax et al., 2015). Additionally, SCCT models direct and indirect effects of various factors on choice goals, such as students' major plans. However, in this study, the methodological approach precluded our ability to examine direct and indirect effects. Therefore, future research on this topic should employ additional techniques, such as structural equation modeling.

Summary and discussion

This study documents the ebb and flow of male and female intended computer science majors over a 40-year period, from 1971 through 2011. By taking into account the historical context during which these shifts occurred, it is possible to draw important comparisons between men's and women's participation in the field in relation to the post-Sputnik computing boom and subsequent decline and then the dot-com boom and accompanying "bust." These results underscore present-day concerns over a shortage of trained computer scientists by revealing both a significant downturn between the late 1990s and 2011 and a persistent, sizeable underrepresentation of women.

While one may expect fluctuations in students' career interests as opportunities in the labor market change over time, computer science is noteworthy in that the observed patterns are so markedly different for women and men, especially in the past two decades. It is important to consider why patterns of computer science interest would be fairly similar for women and men in the 1970s and 1980s but would take a different turn in the 1990s and beyond. As suggested by Ensmenger (2012), in the early days of computer programming, computer science was not yet defined as a science but was believed to be more clerical in nature. However, as demand for individuals with programming skills increased, computer science also sought legitimacy as a field, in large part by defining itself as a science. In doing so, computer science distanced itself from skill sets traditionally thought to be well suited to women and sought to align itself with other science fields, like engineering, that had strong masculine connotations. Additionally, in the mid-1980s, the narrative around computing became gendered, such that tech companies and the media portrayed computing as a predominantly male enterprise (e.g., personal computers were initially marketed as toys for men and boys; Henn, 2014). Further, media depictions of computing (e.g., films like *Revenge of the*

Nerds and *Weird Science*) emphasized the male computer nerd/geek stereotype (Henn, 2014). Hence, computer science increasingly became a field predominantly associated with men at the same time that opportunities for careers in computer programming expanded. Finally, women's declining representation in computing during the dot-com "bubble" of the late 1990s is owed in part to an increase in weed-out courses that, although intended to manage growing enrollments, ultimately discouraged disproportionate numbers of women from computer science (Aspray, 2016). Research should continue to investigate broader influences on women's participation in computing, particularly given recent major efforts to make computing more appealing to young women.

This study also used logistic regression and decomposition to examine predictors of students' aspirations to major in computer science, whether they differ by gender or have changed over time. Of the 38 independent variables, 10 reflect attributes of prospective computer science majors that are the same for women and men and that have remained stable forces for the past four decades. Among these consistent predictors of majoring in computer science, a few merit additional consideration and are discussed in turn in the following paragraphs.

First is the persistent negative association between social activist values and the pursuit of computing careers; women and men who place greater importance on helping others and effecting social change are less likely to pursue computer science in college. Other research has also documented the negative effect of social activist orientations on students' STEM-related decisions, especially among women (Weinberger, 2004; Wilson, 2002). Further, the decomposition analysis showed that women's relatively stronger social activist orientation serves as one of the key explanations for the gender gap in computing.

Another stable but noteworthy finding relates to the role of race. Here we found that for both women and men, being Asian American or African American was associated with a greater likelihood of majoring in computer science. While the result for Asian students is consistent with longstanding patterns of racial representation in STEM fields (NCES, 2012), the result for African American students counters a common description of this population as underrepresented in STEM. This discrepancy is owed to the fact that among all STEM fields, computer science produces the greatest proportion of African American bachelor's degree holders at rates even higher than their representation among degree holders from all fields; this is especially true among women, as discussed earlier. Although these results appear to bode well for diversifying computer science, we must also be cognizant of the current trajectory of African American women's representation in computer science: The proportion of female computer science bachelor's degree earners who are African American peaked in 2006 at 21.2% but fell steadily to 16.7% by 2012.

Other noteworthy results reflect variables for which salience has changed over time for one or both genders. Of note is the role of students' goal of making theoretical contributions to science. Across all years, scientific orientations positively predicted both men's and women's intent to major in computer science. Although this relationship has become more salient over time for women, the fact is that women consistently rate their scientific goals lower than men. As the decomposition revealed, women's consistently lower scores on this variable are a key explanation for the gender gap among students who plan to major in computer science. Thus, having a strong theoretical commitment to science encourages students to pursue computer science, but women's lower scores on this variable serve to reinforce the gender disparity in computing.

Some regression results revealed positive trends in attracting women to the computer science major. For example, we found that although women's tendency toward lower math self-concept than men explained a sizeable portion of the gender gap in intent to major in computer science, the salience of math self-concept is weakening over time. This shift is especially important for women because it suggests that having lower confidence in math abilities is less of a deterrent to their plans to pursue computer science.

Additionally, having an artistic orientation, which our analysis showed is a deterrent to pursuing computer science for both genders, has over time become a weaker predictor for women. This finding indicates that women who view themselves as creative or artistic are becoming less likely to avoid computer science. This trend may due to the increasing applicability of a computer science degree to the arts in areas such as music, film, or design (Takahashi, 2013), which may appeal to women or provide a new lens through which to view computer science. Though we have not yet reached a point where artistically and creatively oriented students are *more* inclined to major in computer science than other fields, for women, there is at least a broadening of the computer science pool to include more artistic and creative types than in years past.

Implications

As summarized, the findings of this study suggest that while some of the traditional explanations for the gender gap in computer science continue to hold true, there are distinctive shifts in *who* pursues computer science and *why* some students may be particularly interested in or dissuaded from the major. As scholars, college administrators, policymakers, and the American public alike seek explanations and solutions for the gender gap in computer science, the findings from this study have important implications that can inform research and practice.

This study contributes in many ways to existing scholarship and also serves as a springboard for future research. First, unlike previous studies that have considered STEM fields in the aggregate, this study examined a variety of factors that predict college students' intention to pursue the computer science major specifically. The findings from this study support such an approach, as computer science as a field has nuances that make it distinct from other STEM fields. For example, we found that computer science increasingly attracts lower-achieving students, relative to other fields, most notably among men. This finding is interesting given that previous studies have shown that other STEM fields (such as engineering) tend to attract the highest-achieving students (Sax et al., 2016). Hence, future research should continue to focus its efforts on studying computer science separately from other STEM fields.

Further, this study demonstrates the importance of examining the gender gap in computer science *over time*. The trend analysis revealed a persistent gender gap that is particularly pronounced at times of major growth in the computing industry, an insight that might have been overlooked without the inclusion of longitudinal data. Additionally, by including time elements in both the logistic regression and decomposition analysis, our analyses showed that there have been distinct shifts in the type of student, both male and female, who considers a degree in computer science and that some of the most important explanations for the gender gap in computer science, notably math self-confidence, have become markedly less important in recent years. Therefore, future research should continue to look at participation in computer science within the context of time.

The findings of this study also support the importance of utilizing social-cognitive career theories, such as SCCT, when studying college major choice (Wang, 2013). Although our intention was not to explicitly test SCCT, our study revealed that math self-concept remained the strongest predictor of the choice to enroll in computer science, thereby supporting the importance that SCCT places on self-perceptions and also suggesting the potential to adapt behaviors by adapting self-beliefs (Lent, 2005). Given that many women doubt whether they could succeed in a computer science major (Beyer et al., 2004), future studies should utilize the SCCT framework and include specific measures of self-efficacy related to beliefs in succeeding in the field of computer science.

This study also has important implications for policy and practice, as it can inform efforts to increase women's participation in computer science. Of particular importance is that the salience of some of the longstanding deterrents to women's participation in computing is diminishing. Specifically, two traits that have tended to discourage women from pursuing computer science—their weaker math confidence and stronger artistic orientations relative to men—are now less predictive of the decision to *not* major in computer science. Women's perceptions of computing may be slowly evolving to a point where they view computer science in broader terms, perhaps as more welcoming to those who may not fit the traditional "hacker geek" stereotype. Administrators and policymakers who seek to bring more women into computer science ought to capitalize on these trends by helping more women understand the range of creative opportunities afforded by a computer science degree, rather than trying to recruit women who share traits with men who have traditionally majored in computer science.

Other findings from this study point to a lack of progress in attracting a broader range of women, but they also suggest opportunities to rebrand the field. For example, women's underrepresentation in computer science remains driven by gender differences in certain value orientations—women's stronger commitment to social activism and weaker commitment to making theoretical contributions to science—with the latter influence gaining strength over time. To counter these longstanding forces, efforts to attract more women to computer science will need to highlight the ways in which the field positively impacts communities—locally and globally. These efforts may help to increase interest among women with stronger activist orientations but may also help them to understand the ways in which the field contributes *practically*, not just theoretically, to improving the world around them.

There are many current efforts to rebrand the field in ways consistent with the recommendations presented in this article. An example is Google's Made With Code initiative, which seeks to broaden women's perceptions of computing as a means to attract more women to the field. The Made With Code initiative strives to show girls and young women that code "can be the most creative tool in your toolbox" through a series of online activities that demonstrate code's applicability to art, music, videos, social networks, and society at large. Many colleges and universities have also sought to broaden undergraduate students' perceptions of computer science though new majors that bring together computer science with other degree programs, such as interactive media and digital art. Such efforts are at the heart of the Building, Recruiting, and Inclusion for Diversity (BRAID) Initiative, a program launched in the summer of 2014 by Harvey Mudd College and the Anita Borg Institute. The BRAID Initiative encompasses 15 computer science departments across the country that are intentionally focusing on ways to make computer science more attractive to women. BRAID departments are incorporating a variety of initiatives to diversify their departments, such as creating inclusive classrooms that emphasize the societal benefits of computing and incorporating interdisciplinary curricular pathways to a computer science degree (e.g., a computer science minor and/or double majors). Each of these programs seeks to make computer science welcoming to women, such that more women feel like they belong in the field and can be successful in a computing career.

Conclusion

Increasing the number of young people who major in computer science is vitally important; recruiting women in particular to computing is essential. Given that jobs in the technology industry are among the highest-paying and fastest-growing (BLS, 2014), increasing women's participation in computer science will not only broaden the talent pool in computing but may also help to close the gender-pay gap (St. Rose, 2010). Further, having more women involved in the development of technology will help make the tools of the future more functional for all individuals. This study offers important insights to inform policy around women's participation in computing and provides a strong foundation on which to base future research. At a time when higher education, private companies, nonprofit organizations, and the government are making heavy investments in recruiting more women to computing, studies such as this one are crucial to ensuring that these investments are directed appropriately.

Funding

This research was made possible by a grant from the National Science Foundation, HRD #1135727.

Notes

1. National Science Foundation, National Center for Science and Engineering Statistics, special tabulations of U.S. Department of Education, NCES, Integrated Postsecondary Education Data System, Completions Survey, 2002–12.
2. Because this study was restricted to the items available in the data set, some of the blocks representing SCCT constructs contain a limited number of variables. Still, SCCT proved useful in informing which variables could influence choice behaviors and the order in which the existing variables could be organized temporally for the regression analysis.
3. We included some factors falling just below this threshold due to prior usage in several major studies (e.g., A. W. Astin, 1993; Sax, 2008).
4. The ebb and flow of men's and women's intent to major in computer science maps directly onto national data on degree attainment in computer science, including a widening of the gender gap as computer science degree attainment increased in the 1990s (NSF, 2015).
5. National data on computer science degree attainment has shown a similar downward trajectory in women's representation during the past 25 years, and it reached 15% by 2011 (NSF, 2015).
6. Bias due to omitted variables also contributes to the unexplained portion, but its magnitude cannot be estimated.

7. For instance, self-rated leadership ability explained approximately –5% of the gender gap in 1986. This result can be interpreted to mean that if men and women had equal ratings on leadership self-efficacy, the gender gap in intent to major in computer science would have been 5% larger in that year.
8. Computer science was first listed as a major in the CIRP Freshman Survey in 1970. Data processing or computer programming was later added as a potential major in 1973. These two major options remained as part of the Freshman Survey through the endpoint of this study (2011). In more recent years, the field of computer science has seen the emergence of new areas of study and a splintering of major choice options related to computing such as computer engineering, computer/management information systems, and other math and computer science. With the exception of computer engineering, which first appeared in 2002, these major options did not appear on the survey until after 2011.

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Appendix A

Table A1. Variable list and coding.

Dependent variable	
Intent to major in computer science	Dichotomous: 0 = all others, 1 = data processing/computer programming/computer science
Personal inputs	
Religion (vs. Protestant)	
Catholic	Dichotomous: 0 = "no," 1 = "yes"
Jewish	Dichotomous: 0 = "no," 1 = "yes"
Other	Dichotomous: 0 = "no," 1 = "yes"
None	Dichotomous: 0 = "no," 1 = "yes"
Race (vs. White)	
African American	Dichotomous: 0 = "no," 1 = "yes"
Asian American	Dichotomous: 0 = "no," 1 = "yes"
Latino/Chicano	Dichotomous: 0 = "no," 1 = "yes"
Native American	Dichotomous: 0 = "no," 1 = "yes"
Political orientation	5-point scale: 1 = "far right" to 5 = "far left"
Background characteristics	
Father's education	8-point scale: 1 = "grammar school or less" to 8 = "graduate degree"
Mother's education	8-point scale: 1 = "grammar school or less" to 8 = "graduate degree"
Family income	25-point scale: 1 = "less than $6,000" to 25 = "$250,000 or more"
Father's career: STEM	Dichotomous: 0 = "no," 1 = "yes" (physician, engineer, health professional, nurse, research scientist, or computer programmer)
Mother's career: STEM	Dichotomous: 0 = "no," 1 = "yes" (physician, engineer, health professional, nurse, research scientist, or computer programmer)
Learning experiences	
High school GPA (average grade in H. S.)	8-point scale: 1 = "D" to 8 = "A or A+"
Self-Efficacy	
Self-rated mathematical ability	5-point scale: 1 = "lowest 10%" to 5 = "highest 10%"
Leader personality factor	See **Appendix B**
Scholar personality factor	See **Appendix B**
Outcome Expectations	
Future activity: change major field	4-point scale: 1 = "no chance" to 4 = "very good chance"
Future activity: make at least a 'B' average	4-point scale: 1 = "no chance" to 4 = "very good chance"
Interests	
Goal: develop a meaningful philosophy of life	4-point scale: 1 = "not important" to 4 = "essential"
Goal: make a theoretical contribution to science	4-point scale: 1 = "not important" to 4 = "essential"
Goal: raise a family	4-point scale: 1 = "not important" to 4 = "essential"
Social activist personality factor	See **Appendix B**
Artistic personality factor	See **Appendix B**
Status striver personality factor	See **Appendix B**
Education reasons for choosing a college factor	See **Appendix B**
Extrinsic reasons for choosing a college factor	See **Appendix B**
Contextual influences proximal to choice behavior	
Distance from home	5-point scale: 1 = "10 miles or less" to 5 = "more than 500 miles"

(*Continued*)

Table A1. (Continued).

Dependent variable	
Number of institutions applied	5-point scale: 1 = "none" to 5 = "four or more"
Concern about finances	3-point scale: 1 = "none," 2 = "some," 3 = "major"
Student faculty ratio	
Institutional type: university/ college	Dichotomous: 0 = college, 1 = university
Institutional type: religious/ nonsectarian	Dichotomous: 0 = nonsectarian, 1 = religious
Institutional type: HBCU	Dichotomous: 0 = non-HBCU, 1 = HBCU
Control: public/private	Dichotomous: 0 = private, 1 = public
Choice Goals	
Degree aspirations (vs. bachelor's or less)	
PhD	Dichotomous: 0 = all others, 1 = PhD
Law	Dichotomous: 0 = all others, 1 = law
Medical degree	Dichotomous: 0 = all others, 1 = medical
Master's degree/MDiv	Dichotomous: 0 = all others, 1 = master's or MDiv

Note. STEM = science, technology, engineering, and math; GPA = grade point average; HBCU = Historically Black Colleges and Universities.

Appendix B. Factor variables, loadings, and reliabilities.

	Factor loading	
Factor	Men	Women
Leader personality	α = .66	α = .65
Self-rating: drive to achieve	.72	.71
Self-rating: leadership ability	.83	.83
Self-rating: self-confidence (social)	.77	.75
Scholar personality	α = .64	α = .64
Self-rated: academic ability	.80	.79
Self-rated: self-confidence (intellectual)	.78	.78
Self-rated: writing ability	.72	.73
Social activist personality	α = .76	α = .72
Goal: influence social values	.77	.74
Goal: participate in a community action program	.76	.75
Goal: help others in difficulty	.65	.61
Goal: influence the political structure	.72	.69
Goal: become involved in programs to clean up the environment	.67	.64
Artistic personality	α = .72	α = .69
Goal: create artistic work	.83	.82
Self-rated: artistic ability	.66	.72
Goal: write original works	.75	.67
Goal: become accomplished in the performing arts	.73	.66
Status striver personality	α = .64	α = .64
Goal: obtain recognition from colleagues	.78	.78
Goal: be very well-off financially	.64	.64
Goal: become authority in my field	.75	.74
Goal: be successful in a business of my own	.62	.62
Education reasons for choosing college	α = .63	α = .60
Reason: to gain a general education and appreciation of ideas	.79	.76
Reason: to make me a more cultured person	.78	.77
Reason: to learn more about things that interest me	.73	.73
Extrinsic reasons for choosing college	α = .67	α = .66
Reason: to be able to get a better job	.87	.86
Reason: to be able to make more money	.87	.86