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The role of college knowledge and proactive behavior on participation in cocurricular activities

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Abstract

Background: Demographic characteristics are known to influence participation in cocurricular activities. Less studied are the effects of other background characteristics.

Purpose: We hypothesize that considering college knowledge and students' proactive behaviors in tandem with demographics provides better models for predicting such participation.

Method: We developed a questionnaire and administered it to 3,618 domestic third- and fourth-year undergraduate engineering students at a large public R1 Midwestern university, yielding 860 responses. Logistic regression models predicting five types of cocurricular participation were constructed with demographic characteristics, college knowledge, and proactive behaviors in all combinations as predictors.

Results: Four of five types of cocurricular participation were better modeled using factors beyond demographics. Two were better modeled using only proactive behavior as predictors and two were better modeled using demographics in combination with either college knowledge or proactive behavior. Only one type of participation could be best predicted by demographics alone.

Conclusions: These findings contribute quantitative evidence establishing relationships between participation in engineering cocurricular activities and a wider range of factors than previously reported. Furthermore, they provide guidance for creating intervention programs because, unlike demographics, college knowledge and proactive behavior can be shaped by either the individual or the institution.

KEYWORDS
cocurricular, engagement, precollege preparation, quantitative, socialization

1 | INTRODUCTION

Students' experiences in college, both in and out of the classroom, can have a significant impact on their success during college and after. For example, results from the National Survey of Student Engagement (NSSE, 2018) consistently show positive relationships between participation in cocurricular activities and academic performance. These trends have been borne out both in high school (Eccles & Barber, 1999) and higher education (Kuh, 1993). Perhaps the most commonly studied consequence of participation in cocurricular activities is the concomitant increase in persistence to graduation (Kuh, 1993; Plett et al., 2011; Ross & McGrade, 2016; Simmons et al., 2017; Wassenaar & Major, 2017). Other outcomes examined include sense of belonging (Allendoerfer et al., 2012; Lounsbury & DeNeui, 1995), communication skills (Carter et al., 2016; Kinoshita et al., 2015; Ro & Knight, 2016), leadership skills, teamwork, and engineering design (Kinoshita et al., 2015).

Patterns of participation are often related to such student demographic characteristics as sex, race, ethnicity, and socioeconomic status (SES). For instance, several studies in higher education overall (Bergen-Cico & Viscomi, 2013; Kuh et al., 2006) and in the engineering education literature in particular (Chachra et al., 2009; Simmons, Van Mullekom, & Ohland, 2018; Simmons, Ye, et al., 2018) have shown that women tend to be more engaged in activities other than school work while other studies have reported that first-generation college students are less likely to participate in these types of activities (Lundberg et al., 2007; Manley Lima, 2014; Pascarella et al., 2004; Pike et al., 2003). Tan and Pope (2007) noted that even though some students may recognize the importance of participating in cocurricular activities, other factors such as work, academic pressures, or a simple lack of interest inhibit their participation. These trends are also borne out in engineering with first-generation students and students from low-income families reporting lower participation in out-of-class activities (Simmons, Ye, et al., 2018).

One possible explanation of why certain demographic groups participate more in cocurricular activities is that the experiences they had prior to college established the importance of such activities for their future success in college (Hooker & Brand, 2010). Participation in science, technology, engineering, and mathematics (STEM) focused outreach activities during middle and high school increases self-efficacy in engineering once in college (Fantz et al., 2011; Ozogul et al., 2018; Ralston et al., 2012; Zhou et al., 2017). Furthermore, taking preengineering and advanced placement (AP) courses in high school is linked to higher probabilities of declaring an engineering major (Phelps et al., 2018; Tyson et al., 2011) as is high-school involvement in multiple STEM-focused clubs (Sahin, 2013). However, little is known about whether participation in these types of activities before college leads to participation in cocurricular activities during college.

While the root causes of these differences in participation patterns are not completely known, evidence suggests that socialization, the way in which individuals learn to behave in particular situations and environments, plays a key role. Seymour (1999) suggests that differences in how men and women are socialized before and during college strongly impact enrollment rates and persistence in STEM fields. Women are more likely to enroll in science and engineering courses if someone close to them is already in a STEM field. However, they also report that the impersonal nature of many STEM classes and lack of direct encouragement from faculty are active discouragements and they encounter less resistance from family members if they voice the desire to change majors. Tinto (1999) found that learning communities in which students coregister for courses or participate in other cohort-building activities strongly enhance student learning and persistence, suggesting that these positive outcomes are due to students' academic and social integration via these communities. Several studies have shown that specific groups of students who participate in these programs fare better than those who do not including first-generation students (Inkelas et al., 2007), Black students (Maton et al., 2000), and women (Allen, 1999; Brainard & Carlin, 1998).

The literature shows that participation in activities outside of the classroom has various benefits for students and that factors such as demographics are related to patterns of participation in cocurricular activities. The literature also suggests that precollege experiences and socialization may positively influence outcomes. However, few studies establish a quantitative relationship of either with participation in cocurricular activities. Therefore, the purpose of this work is to examine quantitatively how demographics, precollege experiences, and socialization once students arrive on campus are related to student participation in cocurricular activities.

2 | CONCEPTUAL FRAMEWORK: WEIDMAN'S MODEL OF UNDERGRADUATE SOCIALIZATION

Our conceptual framework is based on Weidman's model of undergraduate socialization (Weidman, 1989), an extension of Astin's input-environment-output (IEO) model of student involvement (Astin, 1984). Astin's basic IEO model hypothesizes that both students' background characteristics (the inputs) and their experiences while in college (the environment) influence collegiate outputs such as student attitudes, knowledge, beliefs, and values. This model has served as a template for a wide range of studies on college outcomes including academic, social, and personal competence (Reason et al., 2006; Strauss & Terenzini, 2007); persistence (Milem & Berger, 1997); ethical development (Finelli et al., 2012); and many others.

Weidman (1989) built on the theories of student development proposed by Astin (1984) as well as Chickering (Chickering et al., 1969) and Tinto (1975). Using a modified IEO template, Weidman argued that socialization is a useful framework for understanding college impact (Figure 1), recognizing that upon entering college students are influenced by various socializing groups including peers, faculty, and parents. His conceptual framework has been applied in a variety of contexts including graduate education (Weidman et al., 2003; Weidman & Stein, 2003), campus diversity (Antonio, 2001), and the influence of parents during college (Wintre & Yaffe, 2000), among others.

The major components of Weidman's model are indicated in Figure 1 as capitalized text. Like Astin, Weidman hypothesizes that student background characteristics—which may include characteristics such as sex and ethnicity as well as other precollege personal attributes—have both direct and indirect effects on socialization outcomes (e.g., postcollege career choices, aspirations, and values) mediated by college environment. Weidman's conceptual framework identifies two categories of the collegiate environment: socialization processes and normative contexts. Socialization processes are those processes through which the internalization of community norms, ideologies, and expectations occur within institutional settings. Weidman considers three of the most salient socialization processes to be the sentiment and frequency of interpersonal interactions, students' subjective assessments of their own experiences in college, and the degree of academic and social integration. Normative contexts are the various academic and social settings in which students experience "varying degrees of normative pressure" in the college environment (Weidman, 1989, p. 304). Weidman broadly categorizes both academic and social collegiate normative contexts as including academic departments, student residences, and extracurricular activities. His model also considers the influence of normative pressures outside of the college experience. In the original model, Weidman recognized the direct and indirect influence of parents on their college-going children before, during, and after college via their own socioeconomic status and expectations. More recently, he (Weidman, 2006) expanded this influence to include extended family and friends, labeling it Personal Communities in the model. He also recognized the influence of nonfamilial communities or occupational communities such as employers and community organizations.

For our research, we adapted and operationalized Weidman's framework, shown in Figure 1 as lowercase text. The proposed model like Weidman's original conceptual framework captures the interactions between background characteristics, the college environment (comprising normative contexts and socialization processes), socialization outcomes, personal communities, and occupational communities. We propose these three adaptations to Weidman's model to better capture both the background characteristics with which students enter college and the specific socialization processes that students experience and demonstrate during their college years.

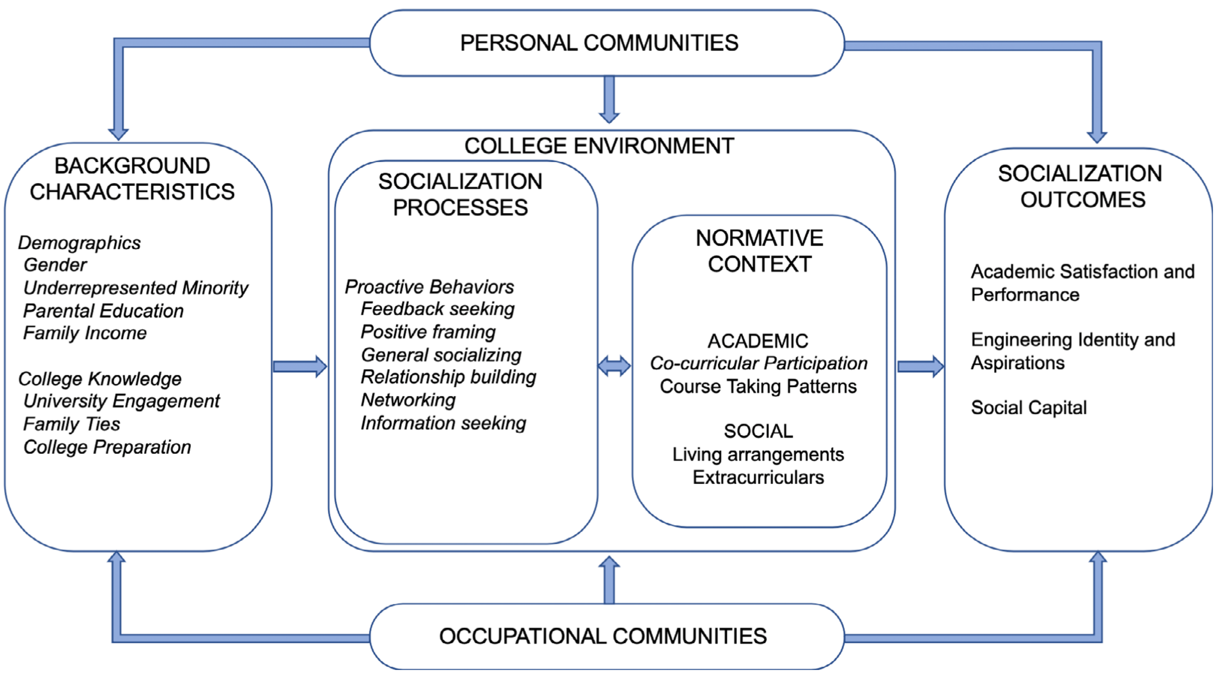

FIGURE 1 Student participation and socialization mechanisms model. Capitalized text represents the main elements of Weidman's model (1989); normal text indicates our adaptions to the model; italicized text denotes the factors considered in our research questions [Color figure can be viewed at wileyonlinelibrary.com]

First, we establish additional components for background characteristics. Weidman suggested broad categories, but we more specifically classify them into two distinct categories: demographic characteristics—including sex, underrepresented minority status, and socioeconomic indicators—and college knowledge characteristics—students' precollege engagement with the university, family ties to the university, and college preparatory experiences (Hooker & Brand, 2010; York-Anderson & Bowman, 1991). We chose to distinguish them because demographics are features that are largely out of the student's control while college knowledge relates to behavior.

Second, we include specific socialization mechanisms adapted from the organizational behavior literature, namely proactive behaviors (shown in Figure 1) and institutional tactics (not shown in Figure 1 for reasons described below), to better understand how students perceive and experience the process of socialization in the college environment. While Weidman's model provides a useful conceptual framework for understanding the process of socialization students undergo as they enter and move through college, it does not provide a means to measure socialization explicitly for empirical validation. In studies of organizational behavior, the process of socialization has been operationalized in two primary ways: as organization-driven institutional tactics (Jones, 1986; Van Maanen & Schein, 1979) and as individual-driven proactive behaviors (Ashford & Black, 1996).

Proactive behaviors are actions taken by newcomers to learn about the expectations, norms, values, and rules within their new organizational contexts (Ashford & Black, 1996). This concept was originally developed in the organizational behavior literature to study newcomer adjustment in the workplace, but it has been adapted for higher education. For example, Wang et al. (2014) examined how student proactive behaviors mediate the pathways from various personality traits to outcomes such as GPA and extracurricular participation. Institutional tactics, which describe how organizations socialize newcomers, were first proposed by Van Maanen and Schein (1979) and then later refined and operationalized by Jones (1986). Our previous work studying these two socialization processes shows that the proactive behaviors fit the model well while institutional tactics do not (Brennan-Wydra et al., 2020). Thus, we focused our analysis only on the proactive behaviors scale in this article.

Third, we posit that within the college environment, the socialization processes that students experience as they enter college influence later engagement with certain normative contexts such as participation in cocurricular activities and research. Weidman, on the other hand, made no assumptions about how socialization processes and normative contexts may or may not influence each other. The validity of these additions to the model, namely the introduction of college knowledge as a background characteristic, specific socialization mechanisms, and the relationships among them, has been examined in previous papers (Brennan-Wydra et al., 2019; Brennan-Wydra et al., 2020; Henderson et al., 2018, 2019). This model also allows us to examine how all these factors impact a wide range of socialization outcomes. Figure 1 lists the outcomes we chose to examine that have been described and validated elsewhere (Millunchick & Zhou, 2020a, 2020b).

In this work, we examine the relationships between students' background characteristics (including demographics and college knowledge) and the proactive behaviors students display in their first year with their participation in engineering-related cocurricular organizations and research. While it has already been shown that demographic characteristics are related to participation in cocurricular activities in engineering (e.g., Simmons & Groen, 2018; Simmons, Van Mullekom, & Ohland, 2018; Simmons, Ye, et al., 2018), we wish to establish whether there are also relationships between participation and college knowledge and between participation and proactive behaviors. Understanding these relationships may help explain and predict student behaviors, experiences, and outcomes in college. Given the positive benefits associated with participating in cocurricular activities in college, understanding the factors that influence student participation may allow engineering educators to encourage more students to participate. The results from this study may also aid the design of targeted interventions to improve the involvement of certain segments of the undergraduate engineering student population, increasing the likelihood of their success.

3 | RESEARCH QUESTIONS

The purpose of this work is to examine how demographics, college knowledge, and socialization once students arrive on campus are related to student participation in cocurricular activities. We investigate the following research questions:

RQ1: Are demographics (D), college knowledge (CK), and/or proactive behaviors (PB) significant predictors of students' cocurricular participation and/or participation in research?

RQ2: What combination of predictors leads to the best model to predict participation in activities such as cocurricular participation and/or participation in research?

Seven different combinations of the predictors were considered: each predictor taken separately (D, CK, PB), predictors taken in pairs (D + CK, D + PB, CK + PB), and all predictors taken together (D + CK + PB).

4 | INSTITUTIONAL CONTEXT

The institution in our study is a large public R1 university in the Midwest. It is highly selective with an acceptance rate of less than 25%. It has a large undergraduate engineering population (>5000 students) that draws from its home state, from across the country (~49% out-of-state students), and from around the world (~10% international students). It offers Bachelor of Science, Master's, and Doctoral degrees in a wide range of engineering disciplines. Incoming first-year engineering students are not admitted into specific majors so the college of engineering offers a variety of programs and activities to orient students to the college, including a formal orientation, required and elective courses, and campus-wide fairs and activities.

5 | MEASURES

We conducted a survey of undergraduate students majoring in engineering using a survey instrument based on our operationalization of our conceptual model (Figure 1). As we are interested in learning about patterns of participation and how students come to participate in various cocurricular activities, we focused on third- and fourth-year students who had time to adjust to college life and settle into their normative contexts. The survey instrument consists of three sections: background characteristics, college environment, and socialization outcomes. In this article, we focus only on background characteristics (demographics and college knowledge), proactive behavior, and cocurricular participation as shown in Figure 1.

We invited all third- and fourth-year domestic undergraduate engineering students ($n = 3618$) to complete an online survey with 931 students responding, yielding a response rate of 25.7%. Fifty-eight students abandoned the survey in the middle of the session, and 13 were missing responses for entire blocks of questions rather than just a few missing items. A total of 71 students (7.6%) were removed from the sample, which is less than the 10% threshold set by Bennett (2001). Thus, the sample for this study includes 860 domestic undergraduate engineering students or approximately 23% of the third- and fourth-year undergraduate engineering student population at the university.

6 | BACKGROUND CHARACTERISTICS

6.1 | Demographics

Demographics were taken from an institutional database and included measures of sex, ethnicity, and SES. Weidman's framework specifies "gender" while we focus on "sex" in this work to distinguish between biological sex and gender identity, which can be fluid. Consistent with Weidman (1989), SES was operationalized as parental educational attainment and annual family income. Parental educational attainment was coded dichotomously to indicate first-generation status, which was assigned if the highest level of parental education was less than a bachelor's degree. Similarly, we recoded annual gross family income as a categorical variable indicating low-, middle-, and high-income status. Students who reported that their families made less than $75,000 annually were classified as low income because many of them qualify for full financial support. Those making more than $200,000 annually were classified as high income, many of whom do not qualify for any financial aid. The remaining students who had an estimated family income between $75,000 and $200,000 comprised the middle-income reference category. The annual gross family income variable was taken from the institutional database, which was self-reported on students' college applications. Any missing data were reclassified as high income in accordance with the standard policy of the institution's Office of Enrollment Management based on unpublished analysis of Free Application for Federal Student Aid data.

Table 1 presents demographics drawn from institutional databases for our study sample and the 3618 domestic students who received an invitation to take the survey. Also included are estimates of the national population of

TABLE 1 Demographics of the study sample, sampling frame, and national population of domestic undergraduate students majoring in engineering

Demographics	Survey sample (%) $n = 860$	Sampling frame (%) $n = 3618$	NCES estimates (%)	
			All institutions	Research universities
Sex				
Female	356 (41.4)	927 (25.6)	(22.5)	(21.1)
Male	504 (58.6)	2691 (74.4)	(77.5)	(78.9)
Race/ethnicity				
Asian/Asian American	253 (29.4)	900 (24.9)	(10.4)	(11.0)
Black/African American	23 (2.7)	121 (3.3)	(6.3)	(6.6)
Hispanic/Latino	47 (5.5)	203 (5.6)	(12.6)	(13.0)
Native American	14 (1.6)	36 (1.0)	(0.5)	(–)
Multiracial or multiethnic	93 (10.8)	324 (9.0)	(3.9)	(4.6)
White	571 (66.4)	2471 (68.3)	(66.2)	(64.6)
Socioeconomic status				
Family income <$75 K	136 (15.8)	586 (16.2)	(45.5)[a]	(36.5)[a]
Family income >$200 K	387 (45.0)	1605 (44.3)	(20.4)[a,b]	(23.6)[a,b]
Parental ed. < bachelor's	106 (12.3)	525 (14.5)	(34.0)	(29.8)
Other variables				
Senior year age ≥ 24	6 (0.7)	127 (3.5)	(28.5)	(22.2)
Student veteran	1 (0.1)	21 (0.6)	(3.5)	(1.6)

Note: National data from the National Center for Education Statistics (NCES, 2018), U.S. Department of Education, for graduating seniors from a bachelor's degree program in 2015–2016 who are U.S. citizens or permanent residents with a major field of study in engineering or engineering technology.
[a]Estimate represents percentage of students who are financially dependent on their families. Financially independent students who comprise 45.9% of the national engineering student population and 19.2% of the engineering student population at research universities as reported by the NCES are excluded from this estimate.
[b]Estimate represents percentage of students with a family income of $150,000 or more, the highest income bracket reported by the NCES.

engineering students at all institutions (second column from right) and at Carnegie-classified research (R1 and R2) institutions (far right column) obtained from the National Center for Education Statistics (NCES; 2018). The database items for each characteristic are indicated in the table. The sample was approximately representative of the population of domestic third- and fourth-year undergraduate engineering students at the institution under investigation along with race/ethnicity, parental education level, and family income. Students identifying as female were overrepresented in the study sample compared with the population of engineering students at the university, consistent with the finding of Porter and Whitcomb (2005) that female college students are more likely to take part in surveys. In the remainder of the article, we refer to Black/African American, Hispanic/Latino, Native American, and multiracial or multiethnic together as underrepresented minorities (URMs) due to their small numbers. Neither our survey sample nor the sampling frame is entirely representative of the general college-going population or even of the population attending research institutions, both of which tend to have a larger proportion of underrepresented, low-income, first-generation, and nontraditional students. The sample of older and veteran students was very small, so we did not consider these variables here.

6.2 | College knowledge

As outlined in the previous section, we collected information about students' precollege engagement with the university, family ties to the university, and college preparatory experiences—collectively referred to as college knowledge—by adapting questions from a precollege survey from Duke University as part of the Campus Life and Learning Project Bryant et al. (2006). Our instrument included a list of 14 statements about a variety of resources and experiences and asked respondents to "indicate all of the things that were true for you while you were preparing for and applying to

TABLE 2 Item responses for 14 college knowledge variables

College knowledge (survey items, grouped post hoc)	n (%)
University engagement	
I attended a university-sponsored recruitment visit.	321 (37.3)
I spoke with a representative of the university.	265 (30.8)
I visited the university's campus.	696 (80.9)
Family ties to the university	
I had family ties to the University (e.g., a family member who worked at the university).	88 (10.2)
I had a family member who graduated from the university.	275 (32.0)
High school college prep	
I took advanced placement (AP) courses.	806 (93.7)
I spoke with a high school counselor about college.	618 (71.9)
I participated in a math, science, or engineering focused club, organization, or camp.	492 (57.2)
College course taking	
I took college courses for credit (high school and/or college credit).	303 (35.2)
I took college courses non-credit.	74 (8.6)
Private college prep	
I had a private tutor for high school classes.	53 (6.2)
I had a private tutor for SAT/ACT preparation.	135 (15.7)
I took SAT/ACT preparation courses (e.g., Kaplan, Princeton Review, etc.).	324 (37.7)
I used a college admissions or educational consultant.	123 (14.3)

college." For convenience, the 14 items were binned into five categories post hoc: university engagement, family ties to the university, high-school college prep, college course taking, and private college prep. However, all analyses were done on individual items. Item text and responses for each of the 14 dichotomous college knowledge variables for our sample of 860 students are shown in Table 2.

We found that associations between demographics and college knowledge variables are not very strong. Table 3 displays phi (ϕ) correlation coefficients among 19 background characteristics (five demographic variables, with the categorical income variable recoded into dichotomous low- and high-income indicators) and 14 college knowledge variables. No pairs of variables were found to have $|\phi| > 0.5$, and only five pairs of variables had $|\phi|$ between 0.35 and 0.50 (indicated with bold text in Table 4). Several correlations are statistically significant to the $p < .05$ level (bolded in Table 4) despite the very low $|\phi|$ values. Unsurprisingly, the majority of high $|\phi|$ values and significant associations are within each post hoc category. Also unsurprising is the significant although relatively small correlation between socioeconomic variables such as family income and parental education and private college preparation items. For instance, high family income is positively associated with having private tutors for high-school classes ($\phi = 0.085$) and ACT/SAT preparation ($\phi = 0.179$) and for taking ACT/SAT preparation courses ($\phi = 0.101$) while low family income is negatively associated with these items ($\phi = -0.070$; $\phi = -0.150$; $\phi = -0.085$).

7 | PROACTIVE BEHAVIORS

Our survey asked students about their experiences with proactive behaviors—actions taken by newcomers to learn about the expectations, norms, values, and rules within their new organizational contexts (Ashford & Black, 1996). We adapted Ashford and Black's (1996) scales measuring proactive behaviors across six dimensions to reflect an undergraduate context: feedback seeking, positive framing, general socializing, relationship building with older students, networking, and information seeking. Examples of survey items pertaining to each are shown in Table 5. We performed confirmatory factor analysis (CFA) to validate our adaptations of the scale using the factor structure and model proposed by the original authors (Ashford & Black, 1996) using Stata/IC 15.1 (StataCorp, 2017). Absolute and incremental fit indices indicated good model fit (Hu & Bentler, 1999): root mean square error of approximation

TABLE 3 Phi (φ) coefficients representing associations between binary student background characteristics

	Demographics					University engagement			Family ties		High school prep			College course taking		Private college prep		
Demographics	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
1. Female	—																	
2. URM	−0.048	—																
3. Family income <$75K	−0.013	**0.093**	—															
4. Family income >$200K	**0.072**	**−0.113**	**−0.398**	—														
5. First generation	0.009	0.059	**0.283**	**−0.142**	—													
University engagement																		
6. Recruitment visit	0.003	0.053	−0.014	−0.004	−0.037	—												
7. Representative	0.016	0.034	0.012	−0.032	**−0.066**	**0.405**	—											
8. Campus visit	**0.097**	0.036	**−0.120**	0.048	**−0.099**	**0.333**	**0.285**											
Family ties																		
9. To university	−0.052	0.005	−0.004	−0.044	−0.016	**0.102**	**0.110**	**0.118**	—									
10. Legacy	0.021	−0.047	**−0.115**	−0.001	−0.062	**0.132**	**0.102**	**0.232**	**0.243**	—								
High school prep																		
11. AP courses	0.041	−0.060	**−0.085**	0.055	**−0.102**	**0.157**	**0.064**	**0.400**	0.048	0.151	—							
12. High school counselor	0.054	0.031	−0.054	0.062	−0.048	**0.250**	**0.255**	**0.351**	**0.075**	**0.147**	**0.371**	—						
13. STEM activities	0.035	0.002	−0.012	0.029	−0.036	**0.150**	**0.214**	**0.250**	0.028	0.045	**0.310**	**0.244**	—					
College course taking																		
14. For credit	−0.032	0.003	0.002	−0.012	0.004	0.030	**0.114**	**0.077**	0.014	−0.052	0.062	**0.077**	**0.159**	—				
15. Not for credit	−0.048	0.011	−0.032	−0.018	0.017	0.037	0.034	0.049	0.026	−0.010	**0.089**	0.039	**0.101**	**0.200**	—			
Private college prep																		
16. High school tutor	0.005	−0.002	**−0.070**	**0.085**	**−0.067**	0.036	**0.111**	−0.010	−0.033	−0.018	0.025	**0.075**	0.064	**0.104**	**0.065**	—		
17. SAT/ACT tutor	0.059	−0.033	**−0.150**	**0.179**	**−0.087**	**0.080**	**0.113**	**0.118**	0.020	0.001	**0.114**	**0.178**	**0.087**	**0.077**	0.024	**0.304**	—	
18. SAT/ACT prep courses	0.005	−0.027	**−0.085**	**0.101**	−0.047	0.053	**0.099**	**0.065**	0.022	0.038	**0.214**	**0.189**	**0.090**	−0.010	0.017	**0.169**	0.026	—
19. College consultant	−0.050	0.023	−0.043	**0.074**	**−0.074**	**0.116**	**0.168**	**0.069**	0.057	0.037	**0.092**	**0.208**	**0.081**	0.044	0.050	**0.219**	**0.223**	**0.159**

Note: Bolded cells represent statistically significant correlations ($p < 0.05$).
Abbreviations: AP, advanced placement; URM, underrepresented minorities; STEM, science, technology, engineering, and mathematics.

(RMSEA) = 0.048, standardized root mean residual (SRMR) = 0.041, comparative fit index (CFI) = 0.960, and Tucker–Lewis index (TLI) = 0.951. Scale reliability coefficients and factor loadings for the six proactive behavior dimensions are all within accepted parameters as shown in Table 4, indicating that the measured variables conform to the theorized constructs of the proactive behaviors scale.

We obtained factor scores for the six proactive behaviors by calculating the unweighted mean of the item responses for each dimension, resulting in a theoretical minimum score of 0 and a theoretical maximum of 6 for each. Summary statistics for the six factor scores are shown in Table 4. All mean factor scores were at or above the neutral score of 3.0 ("Neither agree nor disagree") across scale items. Networking behavior (forming relationships with people outside of engineering) had the highest factor score at 4.14, corresponding to an average score for items in this subscale between

TABLE 4 Mean factor scores and standard deviations for proactive behaviors and factor loadings and scale reliability coefficients (α) for Ashford and Black's (1996) proactive behaviors scales adapted for the undergraduate context ($n = 860$)

Proactive behaviors latent variables and indicators	Mean	α	Standardized estimate	SE
Feedback seeking	3.1 ± 1.4	0.89		
I often sought feedback on my performance after assignments.			0.825	0.014***
I solicited critiques from my professors/instructors.			0.800	0.016***
I often sought feedback on my performance during assignments.			0.827	0.014***
I often asked for professors'/instructors' opinion of my work.			0.809	0.015***
Positive framing	4.4 ± 1.1	0.78		
I tried to see being an engineering student as an opportunity rather than a threat.			0.821	0.020***
I often tried to look on the bright side of things.			0.658	0.025***
I tried to see my engineering major as a challenge rather than a problem.			0.771	0.021
Relationship building	3.1 ± 1.6	0.89		
I tried to spend as much time as I could with more senior students.			0.806	0.015***
I tried to form a good relationship with more senior students.			0.861	0.013***
I worked hard to get to know more senior students.			0.883	0.013***
General socializing	4.0 ± 1.3	0.66		
I attended social gatherings to meet new people.			0.832	0.022***
I participated in social events on campus outside of the college of engineering to meet people.			0.668	0.025***
I attended parties with friends I met in engineering.			0.463	0.031***
Networking	4.1 ± 1.2	0.78		
I started conversations with people from different academic majors than my own.			0.734	0.021***
I tried to socialize with people (faculty, students, or staff) who are not in engineering.			0.770	0.020***
I tried to get to know as many people as possible in non-engineering majors on a personal basis.			0.717	0.022***
Information seeking	3.1 ± 1.3	0.81		
I tried to learn the important policies and procedures of the university.			0.655	0.024***
I tried to learn the official organizational structure of the college of engineering.			0.819	0.018***
I tried to learn the politics of the college of engineering.			0.674	0.023***
I tried to learn the unofficial structure of the college of engineering.			0.735	0.021***

Abbreviation: SE, standard error.
$^{***}p < 0.001$.

TABLE 5 Summary of reported participation in cocurricular organizations and research

Participation	Number (%) $n = 860$	Description
Cocurricular organizations	638 (74.2)	At least one cocurricular organization listed
College-run	113 (13.1)	Official university-run activities, for example, Peer Mentoring, Student Government, Undergraduate Student Advisory Board
Student-run		
Professional societies	281 (32.7)	Student chapters of professional associations, for example, American Society of Mechanical Engineers, Tau Beta Pi
Design and competition teams	395 (45.9)	Collaborative cocurricular project teams, for example, Concrete Canoe Team, Solar Car Team
Identity-based engineering organizations	168 (19.5)	Activities with an identity component, for example, National Society of Black Engineers, Society of Women Engineers
Research	382 (44.4)	Worked on a research project with a faculty member during college

"Somewhat agree" and "Agree." Conversely, feedback-seeking behavior (asking instructors for feedback on performance) had the lowest mean score at 3.06.

8 | PARTICIPATION IN COCURRICULAR ACTIVITIES

To understand students' patterns of cocurricular participation, our survey included questions we created related to involvement in engineering-related cocurricular organizations and research.

8.1 | Participation in engineering-related cocurricular organizations

Students were asked whether they were currently involved or had ever been involved in an engineering-related organization during college. Students who indicated that they had participated in such an organization were then asked to submit the names of no more than the five they were most involved in. We also asked additional questions about their participation in each organization listed including how they became interested in joining the group, what their reasons were for joining, and how active they were in the organization. Results from these questions were analyzed elsewhere (Millunchick & Zhou, 2020a, 2020b).

The engineering-related organizations reported were first classified following a coding scheme for undergraduate engineering student involvement proposed by Mwenesi et al. (2018). Before applying the coding scheme, we removed organizations that were not related to science, math, engineering, or technology (e.g., marching band). The remaining involvements were classified according to the coding scheme as either student-run organizations (e.g., solar car team, Society of Women Engineers) or official college-run activities (e.g., peer-mentoring programs, honors program). We classified each of the reported involvements in student-run organizations into one of three categories—professional societies, identity-based engineering organizations, and design and competition teams—based on their stated mission, goals, and activities as documented in organization constitutions on a university-managed online system for student organizations.

Some cocurricular organizations could be viewed as serving multiple missions or fitting into multiple categories. In this study, the university's chapters of the National Society for Black Engineers (NSBE), the Society of Women Engineers (SWE), and the Society of Hispanic Professional Engineers (SHPE) could be seen as both professional societies and identity-based engineering organizations. Originally, these organizations were coded into both applicable categories, but initial analytic findings showed that patterns of participation in these types of activities tended to more closely mirror those for one category than the other. Specifically, patterns of student involvement with NSBE, SWE, and SHPE were more similar to what we observed for identity-based engineering organizations than for professional societies. These organizations were then reclassified into only one category.

8.2 | Participation in research with a faculty member

Our survey also included two questions about research involvement. First, students were asked whether they had "worked on a research project with a faculty member" during college. Students who indicated that they had were then asked whether the research position was "with a professor in the College of Engineering." Here, we considered students who reported working on any research project regardless of whether it was with an engineering professor because the clear majority of even nonengineering research projects in which engineering students participate has a strong STEM focus. For instance, engineering students often conduct research with chemistry and physics faculty.

Table 5 includes brief descriptions and representative organizations from each of the five categories for cocurricular activities. It shows that among the 860 domestic students in our sample, 638 (74.2%) reported participation in at least one engineering-related cocurricular organization. A total of 1218 involvements with cocurricular organizations were listed representing 134 unique organizations. Of the students who reported participating in cocurricular activities, the mean number of involvements per student was 1.91.

9 | ANALYTIC METHODS

To answer our research questions about the relationships among demographics, college knowledge, proactive behaviors, and cocurricular participation, we constructed and compared a series of multiple logistic regression models. These models contained each of the five types of participation we identified—college-run engineering organization, design and competition teams, identity-based engineering organizations, professional societies, and research with a faculty member—as dichotomous outcomes. All statistical analyses were carried out using Stata/IC 15.1 (StataCorp, 2017).

RQ1 asks whether demographics (D), college knowledge (CK), and/or proactive behaviors (PB) are predictive of cocurricular participation (P). To answer this question, we created three initial logistic regression models for each of the five types of cocurricular participation including each set of predictors separately. We then assessed the models' overall predictive significance by examining the p-values representing the chi-squared (χ^2) tests of significance comparing each model to the null model.

RQ2 asks which combination of predictors results in the best model for each type of participation. Therefore, we created and assessed four additional logistic regression models for each of the five types of cocurricular participation including each set of predictors considered in sets of pairs (D + CK, D + PB, CK + PB) and all predictors together (D + CK + PB).

Model selection is a complex statistical problem with many possible approaches and solutions. Because we needed to make comparisons between models that were not nested (e.g., D and CK + PB), we were unable to use Wald or likelihood-ratio tests to compare our models under a hypothesis-testing framework. McFadden's pseudo-R^2, a commonly used metric for assessing the fit of logistic regression models, was also not acceptable for our purposes because it does not include a penalty for the number of predictors, thus encouraging overfitting. That is, the model with more predictors will always have the larger pseudo-R^2 when comparing two nested models (McFadden, 1974). Instead, we used the Akaike information criterion (AIC) for model selection, which is given by

$$\mathrm{AIC} = 2k - 2\ln(\hat{L})$$

where k is the number of estimated parameters in the model and $(\hat{L})$ is the maximum value of the likelihood function for the model (Burnham & Anderson, 2004). Given a set of models, the one with the lowest AIC is the preferred model. However, models that have AICs within 4 points of the AIC of the preferred model also have strong support for best describing the data (Burnham & Anderson, 2004). In this analysis, we compared the AIC for the models that were found to be significant overall for each type of participation (RQ1) and selected the one with the lowest AIC as the preferred model.

10 | LIMITATIONS

Several factors limit the generalizability of our findings. Perhaps the most important is that this initial work was conducted at a single institution with a population differing significantly from the overall population of engineering students nationwide along demographic lines. For instance, this institution has a higher percentage of Asian students and a lower percentage of Black, Hispanic, and low-income students. While the findings of this research may be generalizable to similarly sized, populated, and resourced schools of engineering, they may not be replicated at schools with higher percentages of underrepresented populations—low-income, first-generation, or nontraditional students (Inkelas et al., 2007; Martin et al., 2013; Tan & Pope, 2007; Young et al., 2014). Future work could include expanding the research to multiple institutions, first to other research (R1 and R2) universities and then to a broader array of types of institutions such as smaller engineering schools and commuter campuses.

A second limitation is that students identifying as female were overrepresented in our survey, comprising 41% of our sample compared with just 26% of the population of undergraduate students in engineering. Although overrepresentation of female students is neither a problem in itself nor unexpected (Porter & Whitcomb, 2005), it may limit the generalizability of our findings to the student population, especially if male and female students differ significantly in terms of either patterns of cocurricular participation or socialization during the first year of college.

Third, we excluded international students (who comprise approximately 10% of the undergraduate student body in the college of engineering) from the study sample because their overall characteristics and available resources make them fundamentally different from domestic students. This population comes from a wide range of countries making it difficult to generalize, especially around college knowledge. For instance, even though we are unaware of any studies in this area, it is not logical to expect a student from China to have access to the same types of college knowledge experiences, such as taking AP courses and visiting the campus prior to attending college, as a student from Canada. In addition, reliable family income data are not available for this population. In the survey sample, these students did not consistently report their income and if the data are available, they are not adjusted for the cost-of-living differences between the home country and the United States. Finally, analysis of our data shows that international students do not respond to the scales of the socialization processes in the same way as domestic students (Brennan-Wydra et al., 2020). This result is not surprising given that the phrasing of the questions may be more idiomatic and/or have different meanings depending on the cultural context (e.g., "learning the ropes") and that international students participate in orientation activities separate from domestic students. Future iterations of this study could endeavor to include college knowledge characteristics relevant to international students.

A fourth potential limitation concerns the way in which we measured student family income. Although the institutional database from which we obtained the other demographic data contains self-reported gross family income, data are missing for approximately 24% of the study sample. Our institution's Office of Enrollment Management developed policies for reclassifying missing data as high income based on internal financial aid data and historical institutional trends, policies that cannot be applied to other institutions.

Finally, several sections of the survey instrument asked the upper-level student respondents to reflect on their experiences before college and during their first year of college. Any retrospective reflection of this nature may introduce measurement error into survey responses as respondents may mistakenly attribute current feelings and experiences to the period being measured (Groves et al., 2009, Chapter 7).

11 | RESULTS

For brevity, we discuss the details of the logistic regression models only for one type of participation: participation in college-run engineering activities. Tables of the models for the remaining types of activities can be found in the Appendix.

RQ1 asks whether demographics (D), college knowledge (CK), and/or proactive behaviors (PB) are significant predictors of students' cocurricular participation in activities such as cocurricular organizations and/or research. Table 6a shows the results of logistic regression models for each of these variables as predictors alone for participation in college-run engineering activities. All three models were found to be significant overall ($p < .05$).

RQ2 asks what combination of predictors leads to the best model for predicting cocurricular participation. Table 6b shows the results of the logistic regression models for each combination of variables as predictors for participation in college-run engineering activities. All four models were found to be significant overall ($p < .01$). To determine which of the significant models provided the best fit, we compared the AIC for all seven models and deemed the model with the lowest AIC to be the preferred model. Table 7 shows the AIC values for each of the statistically significant models for each type of participation examined. The model with the lowest AIC value is underlined. AIC values within 4 points of the minimum AIC are also considered to have a high probability of best describing the data (Burnham & Anderson, 2004) and are bolded in the table. For participation in college-run engineering activities, we found the model containing

TABLE 6a Logistic regression models for participation in college-run engineering activities that include demographics (D), college knowledge (CK), or proactive behaviors (PB) individually as predictors

	D	CK	PB
n	860	860	860
χ^2	14.16	23.96	23.08
Degrees of freedom	5	14	6
p-value	0.015*	0.046*	<0.001***
Pseudo-R^2 value	0.021	0.036	0.035
AIC	666.97	675.17	660.06
Predictors	**Odds ratio (SE)**	**Odds ratio (SE)**	**Odds ratio (SE)**
Demographics			
Female	2.05 (0.42)***	—	—
URM	1.30 (0.43)	—	—
Family income <$75 K	0.73 (0.24)	—	—
Family income >$200 K	0.94 (0.21)	—	—
First generation	1.26 (0.39)	—	—
University engagement			
Recruitment visit	—	1.52 (0.34)	—
Representative	—	0.77 (0.19)	—
Campus visit	—	1.32 (0.42)	—
Family ties			
To university	—	0.87 (0.31)	—
Legacy	—	1.17 (0.26)	—
High-school prep			
AP courses	—	2.12 (1.32)	—
High school counselor	—	1.32 (0.34)	—
STEM activities	—	1.23 (0.27)	—
College course taking			
For credit	—	1.62 (0.35)*	—
Not for credit	—	0.66 (0.27)	—
Private college prep			
High-school tutor	—	0.75 (0.37)	—
SAT/ACT tutor	—	1.33 (0.38)	—
SAT/ACT prep courses	—	1.40 (0.30)	—
College consultant	—	0.51 (0.18)	—
Proactive behaviors			
Feedback seeking	—	—	1.06 (0.09)
Positive framing	—	—	1.10 (0.12)
Relationship building	—	—	0.96 (0.07)
General socializing	—	—	1.46 (0.16)**
Networking	—	—	0.95 (0.10)
Information seeking	—	—	1.06 (0.09)
Constant	0.11 (0.02)***	0.03 (0.02)***	0.02 (0.01)***

Abbreviations: AIC, Akaike information criteria; AP, advanced placement; SE, standard error; STEM, science, technology, engineering, and mathematics; URM, underrepresented minorities.

*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

TABLE 6b Logistic regression models for participation in college-run engineering activities that include demographics (D), college knowledge (CK), or proactive behaviors (PB) in combination as predictors

	D + CK	D + PB	CK + PB	D + CK + PB
n	860	860	860	860
χ^2	38.35	34.95	41.55	54.37
Degrees of freedom	19	11	20	25
p-value	0.005**	<0.001***	0.003**	<0.001***
Pseudo-R^2 value	0.057	0.052	0.0621	0.081
AIC	670.78	658.18	669.58	666.77
Predictors	**Odds ratio (SE)**	**Odds ratio (SE)**	**Odds ratio (SE)**	**Odds ratio (SE)**
Demographics				
Female	2.12 (0.45)***	1.92 (0.40)**	—	2.00 (0.44)**
URM	1.41 (0.47)	1.26 (0.42)	—	1.37 (0.47)
Family income <$75 K	0.80 (0.27)	0.79 (0.26)	—	0.86 (0.29)
Family income >$200 K	0.87 (0.20)	0.87 (0.20)	—	0.82 (0.19)
First generation	1.31 (0.41)	1.46 (0.46)	—	1.45 (0.47)
University engagement				
Recruitment visit	1.56 (0.36)	—	1.51 (0.35)	1.54 (0.36)
Representative	0.77 (0.19)	—	0.74 (0.19)	0.74 (0.19)
Campus visit	1.27 (0.41)	—	1.23 (0.40)	1.21 (0.40)
Family ties				
To university	0.94 (0.34)	—	0.87 (0.31)	0.95 (0.35)
Legacy	1.16 (0.27)	—	1.14 (0.26)	1.13 (0.27)
High-school prep				
AP courses	2.56 (1.63)	—	1.97 (1.23)	2.45 (1.57)
High school counselor	1.28 (0.34)	—	1.19 (0.32)	1.14 (0.30)
STEM activities	1.20 (0.26)	—	1.21 (0.27)	1.19 (0.27)
College course taking				
For credit	1.75 (0.39)*	—	1.56 (0.34)*	1.68 (0.38)*
Not for credit	0.66 (0.27)	—	0.70 (0.28)	0.68 (0.28)
Private college prep				
High-school tutor	0.76 (0.37)	—	0.80 (0.39)	0.79 (0.40)
SAT/ACT tutor	1.32 (0.39)	—	1.19 (0.34)	1.22 (0.36)
SAT/ACT prep courses	1.43 (0.31)	—	1.37 (0.30)	1.42 (0.31)
College consultant	0.55 (0.20)	—	0.54 (0.19)	0.57 (0.21)
Proactive behaviors				
Feedback seeking	—	1.04 (0.08)	1.05 (0.09)	1.03 (0.09)
Positive framing	—	1.12 (0.13)	1.07 (0.12)	1.09 (0.12)
Relationship building	—	0.99 (0.07)	0.96 (0.07)	0.99 (0.07)
General socializing	—	1.43 (0.16)**	1.40 (0.16)**	1.37 (0.16)**
Networking	—	0.95 (0.11)	0.97 (0.11)	0.98 (0.11)
Information seeking	—	1.07 (0.09)	1.07 (0.09)	1.07 (0.09)
Constant	0.02 (0.01)***	0.01 (0.01)***	0.01 (0.01)***	0.00 (0.00)***

Abbreviations: AIC, Akaike information criteria; AP, advanced placement; SE, standard error; STEM, science, technology, engineering, and mathematics; URM, underrepresented minorities.

*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

TABLE 7 Akaike information criteria (AIC) for all models for five types of involvement

	D	CK	PB	D + CK	D + PB	CK + PB	D + CK + PB
College-run	666.97	675.17	**660.06**	670.78	**658.18**	669.58	666.77
Design and competition	—	—	**1184.00**	—	1190.55	—	—
Identity-based	**620.08**	849.67	846.64	**621.95**	**623.87**	846.92	628.04
Professional societies	—	—	**1061.59**	—	1065.96	1070.83	1076.55
Research	—	—	—	**1189.20**	—	**1191.20**	**1191.43**

Note: Underlined text denotes the preferred model and bolding denotes models that have strong support for best describing the data. AIC not reported for models that did not achieve overall significance based on the chi-squared statistic.
Abbreviations: AIC, Akaike information criteria; CK, college knowledge; D, demographics; PB, proactive behaviors.

demographics and proactive behaviors as predictors to have the best fit (AIC = 658.18), but the model containing proactive behaviors alone is also likely. This procedure of model construction and comparison was repeated for each of the remaining four types of participation: design and competition teams (Tables A1a and A1b), identity-based engineering organizations (Tables A2a and A2b), professional societies (Tables A3a and A3b), and research (Tables A4a and A4b).

Our initial hypothesis is that considering college knowledge and students' proactive behaviors in tandem with demographics provides better models for predicting cocurricular participation. However, Table 7 shows that the combination of variables depends on the type of activity. Only participation in research is best predicted by some combination of all the variables. Participation in the other types of cocurricular activities is best predicted by a subset of variables.

12 | DISCUSSION

While there is ample research on the impact of individual factors on cocurricular participation in college, our study extends the literature by considering demographics, college knowledge, and proactive behaviors together to understand quantitatively if these factors predict cocurricular participation. Specifically, we examined seven separate combinations of predictors (D, CK, PB, D + CK, D + PB, CK + PB, D + CK + PB) for predicting cocurricular participation in five types of engineering-related activities: college-run engineering organizations, design and competition teams, identity-based engineering organizations, professional societies, and research with a faculty member. Comparisons of a series of logistic regression models showed that college knowledge and proactive behaviors are useful predictors for participation in all types of activities examined in this study.

12.1 | Demographics as predictors

Our findings show that factors beyond demographics predict cocurricular participation, and, thus, demographics alone cannot be assumed to be a proxy for how certain segments of the student population will experience the college environment. For instance, our findings are consistent with reports (Chachra et al., 2009; Simmons, Van Mullekom, & Ohland, 2018; Simmons, Ye, et al., 2018) that being female is a significant predictor of cocurricular participation. But identifying as female alone is not the best predictor and other factors such as college knowledge and proactive behaviors also come into play.

We find that there was only one type of cocurricular participation for which demographics alone offered the best model fit: identity-based engineering organizations. It is intuitive that participation in organizations such as NSBE, SWE, and SHPE is well predicted by a set of characteristics that includes sex and race and ethnicity. Nonetheless, models containing demographics in combination with either proactive behaviors or college knowledge as predictors for identity-based organizations were also significant and highly likely to be based on the AIC criteria. This result is encouraging because it suggests that students' sex or race is not the only aspect that influences their choice to participate in identity-based organizations and that factors such as participating in STEM activities in high school, for example, also play a role. This may be obvious to some, but, to our knowledge, there is no other work in the literature that has demonstrated this effect quantitatively. In future work, we hope to understand how involvement in cocurricular organizations with an identity component relates to the collegiate outcomes and professional development.

Models including demographics in tandem with other predictors were found to have the best fit for two other types of participation: college-run engineering activities and research. In both cases, sex is a highly significant predictor with the largest odds ratio (OR) of any demographic variable ($OR_{CollegeRun} = 1.92$; $OR_{Research} = 1.47$) where students identifying as female are more likely to participate than their male counterparts. This observation is consistent with Chachra et al. (2009) who found that female engineering students place more importance on and participate more frequently in both engineering and nonengineering-related organizations.

Neither participation in design and competition teams nor professional societies had a significant relationship with demographics overall and sex in particular. This finding contrasts with Simmons, Ye, et al. (2018) who found that these types of activities slightly favor men. It may be that the activities categorized as design and competition teams in this study are more heterogeneous regarding their purpose compared to those reported in Simmons. For instance, we showed in another study that men are more likely to participate in competitive racing teams while women are more likely to participate in design teams focused on sustainability (Gonzalez & Millunchick, 2016). In this study, these organizations were categorized together so that these differences were not detected. On the other hand, it may also be that the influence of sex is simply different in the context of this college-wide single-institution study compared to the single-discipline multi-institutional nature of the Simmons, Ye, et al. (2018) study.

While others have found relationships between cocurricular participation and socioeconomic indicators such as family income or parents' educational level (Lundberg et al., 2007; Manley Lima, 2014; Pascarella et al., 2004; Pike et al., 2003), our study found no significant relationships between these factors. This finding could result because college knowledge variables, which include participation in STEM camps and taking college-level courses, capture a picture of college readiness beyond socioeconomics. For instance, Table 4 shows that there are several weak but statistically significant associations between income and many college knowledge variables. However, it is important to note that the lack of a significant finding in this work does not prove that there are no relationships as our broad-strokes approach taken in this article may have missed more subtle differences in patterns of participation between low- and high-SES students. Similarly, proactive behaviors once students arrive on campus, including general socialization and positive framing, appear to be important predictors for future cocurricular participation. These findings are consistent with other studies. For example, Martin (2015) found that first-generation students who decide to enroll in engineering courses are those who are exposed to resources that enable them to do so once they arrive on campus. In this case, it could be argued that these resources act as an alternative socialization process for first-generation students.

12.2 | College knowledge as predictors

Although considering the college knowledge predictors alone did not offer the best model fit for any of the five types of participation, the model containing college knowledge predictors along with demographic predictors is the best fit for participation in research. Perhaps unsurprisingly, participating in STEM-focused camps, clubs, and activities in high school was associated with a significantly higher likelihood of participating in research (OR = 1.47, SE = 0.22, $p < .01$). However, speaking to a college representative (OR = 0.65, SE = 0.11, $p < .05$) and taking AP courses (OR = 0.53, SE = 0.16, $p < .05$) are associated with a lower likelihood of participation in research.

The models containing only college knowledge variables were found to be significant but did not provide the best fit for two types of participation: college-run engineering activities and identity-based engineering organizations. Taking college courses for credit during high school was associated with a higher likelihood of becoming involved in a college-run engineering activity (OR = 1.62, SE = 0.35, $p < .05$). Participating in STEM-focused camps, clubs, and activities in high school was associated with a significantly higher likelihood of participating in an identity-based engineering organization (OR = 1.48, SE = 0.28, $p < .05$). In addition, we found that participating in a STEM activity in high school was significantly and positively related to research involvement as well as participation in design and competition teams. These findings suggest a link between cocurricular involvement during high school and certain kinds of cocurricular participation in college. It remains to be seen whether these types of participation in high school or college are associated with any benefits on outcomes such as persistence, engineering identity, or postgraduate aspirations. However, Goodman et al. (2002) found no significant relationships between female students' high-school experiences and persistence in engineering majors.

We also identified several college knowledge variables that had negative relationships with participation. Specifically, using a college admissions consultant was associated with a lower likelihood of participation in identity-based organizations in the model containing only college knowledge predictors (OR = 0.31, SE = 0.10, $p < .001$), an effect that persisted even after the variables demographics and proactive behaviors were added. Using a college admissions consultant was also negatively associated with participation in professional societies in the full (D + CK + PB) model (OR = 0.59, SE = 0.14, $p < .05$) and the other models containing college knowledge predictors (D + CK and CK + PB). In addition, taking AP courses was associated with a significantly lower likelihood of participating in research as was speaking with a representative of the university (both $p < .05$). Finally, although none of the models including college knowledge variables was significant overall in predicting participation in design and competition teams, having a tutor for high-school coursework appears to be negatively associated with this type of participation. Upon further investigation, a two-sample, two-sided test of proportions revealed a statistically significant difference in the proportion of students involved in a design and competition team when comparing those who had a tutor for high-school coursework ($M = 0.32$, SD = 0.06) and those who did not ($M = 0.47$, SD = 0.02), $z = 2.09$, $p < .05$.

12.3 | Proactive behaviors as predictors

Four of five types of cocurricular participation (all but research) were predicted by proactive behaviors alone, and participation in both design and competition teams and in professional societies could be best predicted by the model containing only proactive behaviors. For participation in design and competition teams, we found that although the proactive behaviors variables were jointly significant ($p < .05$), none of the individual predictors met this threshold for significance. Nonetheless, all estimated ORs for the predictors were 1.00 or larger suggesting positive relationships between proactive behaviors and involvement in design and competition teams. With respect to professional societies, we found that positive framing (OR = 1.24, SE = 0.10, $p < .01$) and general socializing (OR = 1.31, SE = 0.10, $p < .001$) behaviors were positively associated with participation. General socializing behavior was also significantly associated with participation in college-run engineering activities (OR = 1.46, SE = 0.16, $p < .01$) and identity-based organizations (OR = 1.27, SE = 0.11, $p < .01$) in the models containing only proactive behaviors as predictors. After adding demographics and college knowledge into the model, general socializing remained a significant predictor of participation in college-run engineering activities (OR = 1.37, SE = 0.16, $p < .01$) but not identity-based engineering organizations (OR = 1.15, SE = 0.13, $p > .05$). This result may be explained in part by the fact that students identifying as female engage in more general socializing behavior than their male counterparts (Brennan-Wydra et al., 2019) and that women are more likely than men to participate in identity-based organizations such as SWE.

General socializing behavior, the scale that included items such as "I attended social gatherings to meet new people" and "I participated in social events on campus outside of the college of engineering to meet new people," was a significant predictor of multiple types of cocurricular participation. This finding is consistent with the literature. For example, Wang et al. (2014) found significant positive associations between extraversion, general socializing, and engagement in student activities while Simmons, Van Mullekom, and Ohland (2018) reported that social development and social engagement were among the most commonly reported outcomes of out-of-class participation. The two types of participation not significantly related to general socializing were involvement in design and competition teams and research with a faculty member. These two activities involve more hands-on science/engineering content, which may attract students who are more motivated to participate in those activities to build their technical skills than to make friends. Future work will examine the reasons why students decide to join these types of organization to provide some more context for these findings.

Feedback-seeking behavior also appeared as a significant predictor of multiple types of cocurricular participation. Specifically, we found that feedback seeking was significantly related to a higher likelihood of participation in identity-based engineering organizations in the model containing proactive behaviors only (OR = 1.21, SE = 0.08, $p < .01$) although the magnitude of this effect was reduced to nonsignificance after demographics and college knowledge variables were added to the model (OR = 1.17, SE = 0.10, $p > .05$). Feedback seeking was also positively associated with research participation in the model containing college knowledge and proactive behaviors as predictors (OR = 1.12, SE = 0.06, $p < .05$). It is not surprising that participation in research, which involves close work with faculty, was found to have a positive association with feedback-seeking behavior because the items comprising the feedback-seeking scale are focused on gathering critiques and opinions from professors/instructors (see Table 5). It is not known, however, whether the tendency toward feedback-seeking behavior preceded the involvement in research or whether students who conduct research consequently gain confidence in their abilities to seek feedback from their instructors. Further qualitative work could elucidate the nature of this relationship.

13 | CONCLUSIONS AND FUTURE WORK

Our study adds evidence to the intuition that factors beyond demographics predict participation in cocurricular activities. We categorized five types of activities in which student participate: design and competition teams, professional societies, identity-based organizations, college-run organizations, and research with a faculty member. We explicitly show that most of these types of participation were better modeled using factors beyond demographics. Specifically, participation in design and competition teams and in professional societies was best modeled using only proactive behavior as the predictor. Participation in college-run organizations and research were best predicted using models that considered demographics along with either college knowledge (in the case of research) or proactive behavior (in the case of college-run organizations). Unsurprisingly, only participation in identity-based organizations could be best predicted by demographics alone.

Although we have not established causal relationships linking college knowledge, proactive behaviors, and participation, it is possible that institutions of higher education can modify their tactics to target specific students (e.g., populations deemed at risk for attrition such as URMs first-generation students and low-income students) and move their behaviors toward more beneficial involvements. For example, this work shows the importance of college knowledge items such as participating in STEM camps and taking college-level courses, and it provides reasonable motivation for institutions to continue and/or expand any such efforts to target specific populations, such as low-income, first-generation, and underrepresented groups. Furthermore, institutions can further efforts to socialize first-year students to develop positive framing mindsets through programs such as first-year seminars. In addition, modified orientation programs that focus on developing proactive behaviors may lead to higher rates of participation later in college. Participation in these kinds of activities in turn are likely to have beneficial effects on a variety of outcomes including social capital, engineering identity, and professional aspirations.

In future work, we plan to take a closer look at the relationships between socialization and cocurricular participation. Our survey instrument included several questions about how students found out about the organizations they were involved in as well as their reasons for joining. We will examine relationships between these reasons for joining and proactive behaviors. For example, it is possible that students who reported joining an organization to make friends also engage in more general socializing behavior but not, say, more feedback-seeking behavior.

While this article focused exclusively on the relationships between demographics, college knowledge, proactive behaviors, and cocurricular participation, our future work will examine the relationships between other components of the model (Figure 1). There are several relationships within the normative context—such as course-taking patterns, choice of major, participation in extracurricular activities, and living arrangements—that could be examined in relation to background characteristics and socialization processes. In addition, we will study how all of these relate to student outcomes such academic performance, engineering identity, and postgraduation aspirations. Understanding these relationships will help students, faculty, and university administrators alike understand which college experiences make a difference in the professional formation of engineers.

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APPENDIX

TABLE A1a Logistic regression models for participation in design and competition teams that include demographics (D), college knowledge (CK), or proactive behaviors (PB) individually as predictors

	D	CK	PB
n	860	860	860
χ^2	4.39	16.87	16.51
Degrees of freedom	5	14	6
p-value	0.495	0.263	0.011*
Pseudo-R^2 value	0.004	0.014	0.014
AIC	1194.12	1199.64	1184.00
Predictors	**Odds ratio (SE)**	**Odds ratio (SE)**	**Odds ratio (SE)**
Demographics			
Female	0.94 (0.13)	—	—
URM	0.74 (0.17)	—	—
Family income <$75 K	1.17 (0.25)	—	—
Family income >$200 K	1.08 (0.16)	—	—
First generation	0.74 (0.16)	—	—
University engagement			
Recruitment visit	—	1.14 (0.18)	—
Representative	—	1.15 (0.20)	—
Campus visit	—	0.93 (0.18)	—
Family ties			
To university	—	1.03 (0.24)	—
Legacy	—	0.84 (0.13)	—
High-school prep			
AP courses	—	0.77 (0.23)	—
High school counselor	—	1.12 (0.19)	—
STEM activities	—	1.41 (0.21)	—
College course taking			
For credit	—	0.93 (0.14)	—
Not for credit	—	1.07 (0.27)	—
Private college prep			
High-school tutor	—	0.46 (0.15)*	—
SAT/ACT tutor	—	1.10 (0.23)	—
SAT/ACT prep courses	—	1.08 (0.16)	—
College consultant	—	0.93 (0.20)	—
Proactive behaviors			
Feedback seeking	—	—	1.05 (0.06)
Positive framing	—	—	1.14 (0.08)
Relationship building	—	—	1.09 (0.05)
General socializing	—	—	1.00 (0.07)
Networking	—	—	1.04 (0.08)
Information seeking	—	—	1.04 (0.06)
Constant	0.88 (0.11)	0.86 (0.27)	0.24 (0.09)***

Abbreviations: AIC, Akaike information criteria; AP, advanced placement; SE, standard error; STEM, science, technology, engineering, and mathematics; URM, underrepresented minorities.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

TABLE A1b Logistic regression models for participation in design and competition teams for demographics (D), college knowledge (CK), or proactive behaviors (PB) in combination

	D + CK	D + PB	CK + PB	D + CK + PB
n	860	860	860	860
χ^2	22.32	19.96	30.48	34.85
Degrees of freedom	19	11	20	25
p-value	0.269	0.046*	0.063	0.091
Pseudo-R^2 value	0.019	0.017	0.026	0.029
AIC	1204.19	1190.55	1198.03	1203.66
Predictors	**Odds ratio (SE)**	**Odds ratio (SE)**	**Odds ratio (SE)**	**Odds ratio (SE)**
Demographics				
Female	0.93 (0.13)	0.94 (0.14)	—	0.93 (0.14)
URM	0.69 (0.17)	0.72 (0.17)	—	0.68 (0.17)
Family income <$75 K	1.11 (0.24)	1.18 (0.25)	—	1.12 (0.24)
Family income >$200 K	1.09 (0.17)	1.06 (0.16)	—	1.07 (0.17)
First generation	0.72 (0.16)	0.81 (0.18)	—	0.78 (0.18)
University engagement				
Recruitment visit	1.15 (0.18)	—	1.10 (0.18)	1.11 (0.18)
Representative	1.15 (0.20)	—	1.12 (0.19)	1.11 (0.19)
Campus visit	0.94 (0.18)	—	0.95 (0.19)	0.95 (0.19)
Family ties				
To university	1.03 (0.24)	—	1.02 (0.24)	1.02 (0.24)
Legacy	0.83 (0.13)	—	0.85 (0.13)	0.83 (0.13)
High-school prep				
AP courses	0.70 (0.21)	—	0.75 (0.23)	0.69 (0.21)
High-school counselor	1.14 (0.19)	—	1.07 (0.18)	1.09 (0.19)
STEM activities	1.42 (0.21)*	—	1.38 (0.20)*	1.39 (0.21)*
College course taking				
For credit	0.92 (0.14)	—	0.90 (0.14)	0.89 (0.14)
Not for credit	1.10 (0.28)	—	1.03 (0.26)	1.04 (0.27)
Private college prep				
High-school tutor	0.45 (0.15)*	—	0.48 (0.16)*	0.47 (0.16)*
SAT/ACT tutor	1.07 (0.22)	—	1.07 (0.22)	1.05 (0.22)
SAT/ACT prep courses	1.07 (0.16)	—	1.09 (0.16)	1.08 (0.16)
College consultant	0.91 (0.19)	—	0.90 (0.19)	0.89 (0.19)
Proactive behaviors				
Feedback seeking	—	1.05 (0.06)	1.04 (0.06)	1.04 (0.06)
Positive framing	—	1.16 (0.08)	1.11 (0.08)	1.11 (0.08)
Relationship building	—	1.08 (0.05)	1.09 (0.05)	1.08 (0.05)
General socializing	—	0.99 (0.07)	1.00 (0.07)	0.99 (0.07)
Networking	—	1.04 (0.08)	1.05 (0.08)	1.05 (0.08)
Information seeking	—	1.04 (0.06)	1.04 (0.06)	1.04 (0.06)
Constant	1.00 (0.34)	0.25 (0.09)***	0.29 (0.13)**	0.34 (0.16)*

Abbreviations: AIC, Akaike information criteria; AP, advanced placement; SE, standard error; STEM, science, technology, engineering, and mathematics; URM, underrepresented minorities.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

TABLE A2a Logistic regression models for participation in identity-based organizations that include demographics (D), college knowledge (CK), or proactive behaviors (PB) individually as predictors

	D	CK	PB
n	860	860	860
χ^2	241.41	29.82	16.84
Degrees of freedom	5	14	6
p-value	<0.001***	0.008**	0.010**
Pseudo-R^2 value	0.284	0.035	0.020
AIC	620.08	849.67	846.64
Predictors	**Odds ratio (SE)**	**Odds ratio (SE)**	**Odds ratio (SE)**
Demographics			
Female	26.90 (7.87)***	—	—
URM	5.62 (1.97)***	—	—
Family income <$75 K	0.98 (0.31)	—	—
Family income >$200 K	1.06 (0.24)	—	—
First generation	0.79 (0.25)	—	—
University engagement			
Recruitment visit	—	1.27 (0.25)	—
Representative	—	1.02 (0.21)	—
Campus visit	—	1.38 (0.37)	—
Family ties			
To university	—	0.75 (0.24)	—
Legacy	—	1.02 (0.20)	—
High-school prep			
AP courses	—	0.82 (0.32)	—
High-school counselor	—	1.35 (0.30)	—
STEM activities	—	1.48 (0.28)*	—
College course taking			
For credit	—	0.98 (0.19)	—
Not for credit	—	0.75 (0.26)	—
Private college prep			
High-school tutor	—	1.64 (0.62)	—
SAT/ACT tutor	—	1.13 (0.29)	—
SAT/ACT prep courses	—	1.12 (0.21)	—
College consultant	—	0.31 (0.10)***	—
Proactive behaviors			
Feedback seeking	—	—	1.21 (0.08)**
Positive framing	—	—	0.96 (0.08)
Relationship building	—	—	0.92 (0.05)
General socializing	—	—	1.27 (0.11)**
Networking	—	—	0.89 (0.08)
Information seeking	—	—	0.99 (0.07)
Constant	0.02 (0.01)***	0.14 (0.06)***	0.13 (0.06)***

Abbreviations: AIC, Akaike information criteria; AP, advanced placement; SE, standard error; STEM, science, technology, engineering, and mathematics; URM, underrepresented minorities.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

TABLE A2b Logistic regression models for participation in identity-based organizations for demographics (D), college knowledge (CK), or proactive behaviors (PB) in combination

	D + CK	D + PB	CK + PB	D + CK + PB
n	860	860	860	860
χ^2	267.54	249.61	44.57	273.45
Degrees of freedom	19	11	20	25
p-value	<0.001***	<0.001***	0.001**	<0.001***
Pseudo-R^2 value	0.315	0.294	0.053	0.322
AIC	621.95	623.87	846.92	628.04
Predictors	**Odds ratio (SE)**	**Odds ratio (SE)**	**Odds ratio (SE)**	**Odds ratio (SE)**
Demographics				
Female	29.47 (8.94)***	26.62 (7.84)***	—	28.69 (8.73)***
URM	6.37 (2.28)***	5.80 (2.06)***	—	6.42 (2.32)***
Family income <$75 K	0.97 (0.32)	1.01 (0.32)	—	0.99 (0.33)
Family income >$200 K	1.03 (0.25)	1.08 (0.24)	—	1.07 (0.26)
First generation	0.80 (0.27)	0.83 (0.27)	—	0.81 (0.28)
University engagement				
Recruitment visit	1.47 (0.35)	—	1.30 (0.26)	1.47 (0.35)
Representative	0.98 (0.25)	—	0.96 (0.21)	0.96 (0.25)
Campus visit	1.13 (0.36)	—	1.40 (0.38)	1.20 (0.38)
Family ties				
To university	1.00 (0.37)	—	0.73 (0.24)	0.98 (0.37)
Legacy	1.09 (0.25)	—	0.99 (0.20)	1.03 (0.24)
High-school prep				
AP courses	1.37 (0.64)	—	0.81 (0.32)	1.39 (0.65)
High-school counselor	1.30 (0.33)	—	1.32 (0.29)	1.26 (0.33)
STEM activities	1.56 (0.34)*	—	1.48 (0.28)*	1.49 (0.33)
College course taking				
For credit	1.28 (0.29)	—	0.96 (0.18)	1.23 (0.29)
Not for credit	0.89 (0.38)	—	0.74 (0.25)	0.86 (0.37)
Private college prep				
High-school tutor	1.80 (0.84)	—	1.71 (0.66)	1.84 (0.87)
SAT/ACT tutor	1.00 (0.31)	—	1.01 (0.26)	0.88 (0.28)
SAT/ACT prep courses	1.19 (0.27)	—	1.06 (0.20)	1.16 (0.27)
College consultant	0.28 (0.11)**	—	0.32 (0.11)**	0.29 (0.11)***
Proactive behaviors				
Feedback seeking	—	1.17 (0.10)*	1.22 (0.09)**	1.17 (0.10)
Positive framing	—	0.92 (0.10)	0.94 (0.08)	0.92 (0.10)
Relationship building	—	1.04 (0.07)	0.93 (0.06)	1.02 (0.07)
General socializing	—	1.18 (0.13)	1.23 (0.11)*	1.15 (0.13)
Networking	—	0.87 (0.10)	0.89 (0.08)	0.88 (0.10)
Information seeking	—	0.99 (0.08)	1.00 (0.07)	0.98 (0.09)
Constant	0.01 (0.01)***	0.02 (0.01)***	0.09 (0.05)***	0.01 (0.01)***

Abbreviations: AIC, Akaike information criteria; AP, advanced placement; SE, standard error; STEM, science, technology, engineering, and mathematics; URM, underrepresented minorities.
$^*p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

TABLE A3a Logistic regression models for participation in professional societies that include demographics (D), college knowledge (CK), or proactive behaviors (PB) individually as predictors

	D	CK	PB
n	860	860	860
χ^2	9.12	23.15	39.19
Degrees of freedom	5	14	6
p-value	0.104	0.058	<0.001***
Pseudo-R^2 value	0.008	0.021	0.036
AIC	1089.66	1093.62	1061.59
Predictors	**Odds ratio (SE)**	**Odds ratio (SE)**	**Odds ratio (SE)**
Demographics			
Female	1.23 (0.18)	—	—
URM	0.86 (0.22)	—	—
Family income <$75 K	0.66 (0.15)	—	—
Family income >$200 K	0.97 (0.15)	—	—
First generation	0.75 (0.18)	—	—
University engagement			
Recruitment visit	—	1.01 (0.17)	—
Representative	—	1.40 (0.25)	—
Campus visit	—	1.04 (0.22)	—
Family ties			
To university	—	0.61 (0.16)	—
Legacy	—	1.25 (0.21)	—
High-school prep			
AP courses	—	1.26 (0.43)	—
High-school counselor	—	1.04 (0.19)	—
STEM activities	—	1.10 (0.17)	—
College course taking			
For credit	—	0.81 (0.13)	—
Not for credit	—	1.52 (0.40)	—
Private college prep			
High-school tutor	—	0.58 (0.21)	—
SAT/ACT tutor	—	1.49 (0.32)	—
SAT/ACT prep courses	—	1.02 (0.16)	—
College consultant	—	0.58 (0.14)*	—
Proactive behaviors			
Feedback seeking	—	—	1.04 (0.06)
Positive framing	—	—	1.24 (0.10)**
Relationship building	—	—	1.10 (0.06)
General socializing	—	—	1.31 (0.10)***
Networking	—	—	0.89 (0.07)
Information seeking	—	—	0.99 (0.06)
Constant	0.50 (0.07)***	0.32 (0.12)**	0.07 (0.03)***

Abbreviations: AIC, Akaike information criteria; AP, advanced placement; SE, standard error; STEM, science, technology, engineering, and mathematics; URM, underrepresented minorities.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

TABLE A3b Logistic regression models for participation in professional societies for demographics (D), college knowledge (CK), or proactive behaviors (PB) in combination

	D + CK	**D + PB**	**CK + PB**	**D + CK + PB**
n	860	860	860	860
χ^2	30.15	44.83	57.95	62.23
Degrees of freedom	19	11	20	25
p-value	0.050	<0.001***	<0.001***	<0.001***
Pseudo-R^2 value	0.028	0.041	0.053	0.057
AIC	1096.64	1065.96	1070.83	1076.55
Predictors	**Odds ratio (SE)**	**Odds ratio (SE)**	**Odds ratio (SE)**	**Odds ratio (SE)**
Demographics				
Female	1.18 (0.18)	1.19 (0.18)	—	1.15 (0.18)
URM	0.88 (0.23)	0.83 (0.22)	—	0.86 (0.23)
Family income <$75 K	0.68 (0.16)	0.67 (0.16)	—	0.70 (0.17)
Family income >$200 K	0.99 (0.16)	0.93 (0.15)	—	0.96 (0.16)
First generation	0.75 (0.19)	0.89 (0.22)	—	0.89 (0.23)
University engagement				
Recruitment visit	1.02 (0.17)	—	0.96 (0.17)	0.98 (0.17)
Representative	1.41 (0.26)	—	1.36 (0.25)	1.37 (0.25)
Campus visit	0.97 (0.21)	—	1.01 (0.22)	0.97 (0.21)
Family ties				
To university	0.63 (0.17)	—	0.63 (0.17)	0.64 (0.18)
Legacy	1.20 (0.20)	—	1.22 (0.21)	1.18 (0.20)
High-school prep				
AP courses	1.20 (0.41)	—	1.25 (0.43)	1.20 (0.42)
High-school counselor	1.05 (0.19)	—	0.92 (0.17)	0.93 (0.17)
STEM activities	1.10 (0.17)	—	1.07 (0.17)	1.08 (0.17)
College course taking				
For credit	0.82 (0.13)	—	0.76 (0.13)	0.77 (0.13)
Not for credit	1.55 (0.40)	—	1.55 (0.41)	1.55 (0.42)
Private college prep				
High-school tutor	0.57 (0.20)	—	0.67 (0.25)	0.66 (0.24)
SAT/ACT tutor	1.37 (0.30)	—	1.36 (0.30)	1.29 (0.29)
SAT/ACT prep courses	0.99 (0.16)	—	1.02 (0.16)	1.00 (0.16)
College consultant	0.59 (0.14)*	—	0.58 (0.14)*	0.59 (0.14)*
Proactive behaviors				
Feedback seeking	—	1.03 (0.06)	1.03 (0.06)	1.03 (0.06)
Positive framing	—	1.24 (0.10)**	1.21 (0.10)*	1.21 (0.10)*
Relationship building	—	1.10 (0.06)	1.11 (0.06)	1.10 (0.06)
General socializing	—	1.28 (0.10)**	1.29 (0.10)**	1.28 (0.10)**
Networking	—	0.89 (0.07)	0.91 (0.07)	0.91 (0.07)
Information seeking	—	0.99 (0.06)	1.00 (0.06)	1.01 (0.06)
Constant	0.38 (0.14)*	0.08 (0.03)***	0.06 (0.03)***	0.04)***

Abbreviations: AIC, Akaike information criteria; AP, advanced placement; SE, standard error; STEM, science, technology, engineering, and mathematics; URM, underrepresented minorities.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

TABLE A4a Logistic regression models for participation in research that include demographics (D), college knowledge (CK), or proactive behaviors (PB) individually as predictors

	D	CK	PB
n	860	860	860
χ^2	10.02	22.73	8.55
Degrees of freedom	5	14	6
p-value	0.075	0.065	0.201
Pseudo-R^2 value	0.009	0.019	0.007
AIC	1183.45	1188.74	1186.93
Predictors	**Odds ratio (SE)**	**Odds ratio (SE)**	**Odds ratio (SE)**
Demographics			
Female	1.46 (0.20)**	—	—
URM	1.34 (0.231)	—	—
Family income <$75 K	0.94 (0.20)	—	—
Family income >$200 K	0.98 (0.15)	—	—
First generation	1.28 (0.29)	—	—
University engagement			
Recruitment visit	—	1.14 (0.18)	—
Representative	—	0.65 (0.11)*	—
Campus visit	—	1.07 (0.21)	—
Family ties			
To university	—	0.65 (0.16)	—
Legacy	—	1.16 (0.18)	—
High-school prep			
AP courses	—	0.49 (0.15)*	—
High-school counselor	—	1.10 (0.18)	—
STEM activities	—	1.48 (0.22)**	—
College course taking			
For credit	—	1.15 (0.17)	—
Not for credit	—	1.05 (0.27)	—
Private college prep			
High-school tutor	—	1.35 (0.42)	—
SAT/ACT tutor	—	0.93 (0.19)	—
SAT/ACT prep courses	—	0.98 (0.15)	—
College consultant	—	1.30 (0.27)	—
Proactive behaviors			
Feedback seeking	—	—	1.10 (0.06)
Positive framing	—	—	1.10 (0.08)
Relationship building	—	—	1.03 (0.05)
General socializing	—	—	0.97 (0.07)
Networking	—	—	0.98 (0.07)
Information seeking	—	—	0.92 (0.05)
Constant	0.66 (0.08)**	1.09 (0.35)	0.55 (0.19)

Abbreviations: AIC, Akaike information criteria; AP, advanced placement; SE, standard error; STEM, science, technology, engineering, and mathematics; URM, underrepresented minorities.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

TABLE A4b Logistic regression models for participation in research for demographics (D), college knowledge (CK), or proactive behaviors (PB) in combination

	D + CK	D + PB	CK + PB	D + CK + PB
n	860	860	860	860
χ^2	32.28	19.21	32.27	42.05
Degrees of freedom	19	11	20	25
p-value	0.029*	0.057	0.041*	0.018*
Pseudo-R^2 value	0.027	0.016	0.027	0.036
AIC	1189.20	1186.26	1191.20	1191.43
Predictors	**Odds ratio (SE)**	**Odds ratio (SE)**	**Odds ratio (SE)**	**Odds ratio (SE)**
Demographics				
Female	1.47 (0.21)**	1.48 (0.21)**	—	1.48 (0.22)**
URM	1.28 (0.31)	1.32 (0.31)	—	1.25 (0.30)
Family income <$75 K	0.96 (0.21)	0.95 (0.20)	—	0.98 (0.21)
Family income >$200 K	0.94 (0.15)	0.98 (0.15)	—	0.95 (0.15)
First generation	1.26 (0.28)	1.34 (0.30)	—	1.32 (0.30)
University engagement				
Recruitment visit	1.14 (0.19)	—	1.11 (0.18)	1.11 (0.18)
Representative	0.65 (0.11)*	—	0.63 (0.11)**	0.63 (0.11)**
Campus visit	1.04 (0.20)	—	1.08 (0.21)	1.06 (0.21)
Family ties				
To university	0.67 (0.17)	—	0.66 (0.16)	0.68 (0.17)
Legacy	1.18 (0.19)	—	1.17 (0.19)	1.19 (0.19)
High-school prep				
AP courses	0.53 (0.16)*	—	0.48 (0.15)*	0.52 (0.16)*
High-school counselor	1.08 (0.18)	—	1.10 (0.19)	1.08 (0.18)
STEM activities	1.47 (0.22)**	—	1.48 (0.22)**	1.47 (0.22)*
College course taking				
For credit	1.18 (0.18)	—	1.14 (0.17)	1.17 (0.18)
Not for credit	1.07 (0.27)	—	0.99 (0.25)	1.00 (0.26)
Private college prep				
High-school tutor	1.36 (0.43)	—	1.49 (0.48)	1.51 (0.48)
SAT/ACT tutor	0.93 (0.20)	—	0.90 (0.19)	0.90 (0.19)
SAT/ACT prep courses	0.99 (0.15)	—	0.97 (0.15)	0.98 (0.15)
College consultant	1.36 (0.29)	—	1.32 (0.28)	1.39 (0.30)
Proactive behaviors				
Feedback seeking	—	1.09 (0.06)	1.12 (0.06)*	1.11 (0.06)
Positive framing	—	1.11 (0.08)	1.12 (0.08)	1.13 (0.08)
Relationship building	—	1.11 (0.08)	1.01 (0.05)	1.03 (0.05)
General socializing	—	0.96 (0.07)	0.96 (0.07)	0.95 (0.07)
Networking	—	0.98 (0.07)	0.99 (0.07)	0.99 (0.07)
Information seeking	—	0.92 (0.05)	0.92 (0.05)	0.91 (0.05)
Constant	0.85 (0.29)	0.44 (0.16)*	0.77 (0.35)	0.57 (0.27)

Abbreviations: AIC, Akaike information criteria; AP, advanced placement; SE, standard error; STEM, science, technology, engineering, and mathematics; URM, underrepresented minorities.

*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.