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ORIGINAL ARTICLE

Increasing success in college: Examining the impact of a project-based introductory engineering course

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Abstract

Background: Project-based learning has shown promise in improving learning outcomes for diverse students. However, studies on its impacts have largely focused on the perceptions of students and instructors or students' immediate performance. This study reports the impact of taking a project-based introductory engineering course on students' subsequent academic success.

Purpose/Hypothesis: This quantitative study examines characteristics related to enrollment in the project-based introductory engineering course and subsequent academic performance. We hypothesized that participation in the course would be associated with higher academic performance in subsequent engineering courses. In addition, we examined heterogeneity effects for students traditionally underrepresented in engineering education.

Design/Method: This study utilized data on students' demographics, academic preparation, course enrollment, and course performance from 1,318 engineering students from a large public university in Southern California. Logistic regression analysis with robust standard errors examined enrollment patterns. We applied propensity scores as inverse-probability weights in multiple linear models to calculate the average treatment effect on the treated for participants from the project-based introductory engineering course in five subsequent engineering courses. This analysis was conducted for all students and for selected student subgroups.

Results: Enrollment in the project-based introductory engineering course was positively associated with students' performance in some subsequent engineering courses and did not adversely affect students traditionally underrepresented in engineering.

Conclusions: This study provides an example of a project-based introductory engineering course that can support students' academic success in engineering. The benefits detected for some student populations (e.g., female) are encouraging for broadening engineering pathways.

KEYWORDS

course design, project-based learning, propensity score matching, undergraduate

1 | INTRODUCTION

Enhancing the diversity and quality of graduates in science, technology, engineering, and math (STEM) fields remains a challenge in postsecondary settings (Allen-Ramdial & Campbell, 2014; Olson & Riordan, 2012). The proportion of the female population who enter and graduate in engineering is still significantly lower than that among men (National Science Foundation [NSF], 2017). In 2014, only 19.8% female students (18,626 out of 93,950) received a Bachelor's degree in engineering in the United States (NSF, 2017). The corresponding entering class of full-time, first-year students in 2010 consisted of 21,501 (18.0%) female and 97,643 (82.0%) male students (NSF, 2017). Particularly in engineering fields, the rates of African American and Latino/Hispanic students persisting from first to second year and graduating from engineering majors remain low, relative to Asian and White students (Yoder, 2016). One possible cause that deters students' engineering pathways is the disparity in academic preparation (Griffith, 2010). The majority of underclassmen enter the major with minimal experiential science and engineering experiences (Fox, Weckler, & Thomas, 2015). The disconnect between theory-based learning and practical engineering applications that students face in introductory engineering courses might further disengage learners from engineering programs (Dym, Agogino, Eris, Frey, & Leifer, 2005). To address these pedagogical challenges, project-based learning (PBL) has been integrated into engineering curricula and has shown promise in increasing students' motivation and reducing attrition (Dym et al., 2005; Klingbeil, Mercer, Rattan, Raymer, & Reynolds, 2004; Olds & Miller, 2004). Project-based courses have also been found to help students learn important engineering concepts (Pomalaza-Ráez & Groff, 2003).

This quantitative study reports on the subsequent performance in engineering courses of two cohorts of students who were enrolled in a project-based introductory engineering course over two terms. Students who took the course were exposed to engineering design principles and theoretical knowledge related to assigned projects, as well as product development process, project management and teamwork skills. The study provides an example of a project-based introductory course that might contribute to retaining students and supporting subsequent academic success in engineering. Although studies have looked at college students' perceptions and retention in STEM majors, there is a lack of empirical evidence on other academic performance indicators, such as performance in subsequent STEM courses. This study addresses this gap in the research base for introductory engineering courses. The study contributes to the understanding of engineering pathways (Lee, 2019; Lord, Ohland, Layton, & Camacho, 2019), with a focus on the multiple entry points for students into engineering (i.e., with and without taking an elective introductory course) and their trajectories in their engineering programs.

2 | BACKGROUND

2.1 | Affordances of project-based learning in engineering education

PBL integrates knowledge, practice, and collaboration to address a complex problem or to produce a final artifact—a model, a device, or a design (De Graaf & Kolmos, 2003). PBL experience introduces students to clear and concise design objectives and challenges them to formulate solution strategies in open-ended, learner-directed tasks (Prince & Felder, 2007). This approach allows students to acquire knowledge and skills from multiple topics and knowledge domains and apply them to varied contexts (Hmelo-Silver, 2004). Engineering courses are well suited to incorporate PBL to expose students to core engineering competencies (for examples of PBL in engineering education, see Fox et al., 2015; Guerra, Ulseth, & Kolmos, 2017). Three strategies have been applied to integrate PBL into engineering curricula: (a) add-on changes in a single course, with pre-designed problems reflective of the real world, (b) integration of skills and competencies into existing courses content (e.g., across the undergraduate curriculum), and (c) program rebuilding with an emphasis on societal contexts (Kolmos, 2017). The literature review focuses on the first approach, as this is the strategy adopted by the introductory engineering course that is at the heart of this study.

2.1.1 | Impact on skills and learning beliefs

PBL provides mastery experiences when students develop their understanding and design skills as part of professional practice (Miller, Bohmann, Helton, & Pereira, 2009). Participation in PBL engineering courses has been related to students' perceived gains in interest in engineering, motivation, and skills (Meadows, Fowler, & Hildinger, 2012; Mills & Treagust, 2003). For instance, Mills and Treagust (2003) examined evaluations of project- and problem-based learning programs in engineering and concluded that relative to students in lecture-based courses, students who were exposed to PBL were more motivated and demonstrated enhanced teamwork skills and understanding of engineering problems of practice. First-year students who took a semester of PBL in engineering self-reported an increase in social skills, namely the ability to lead projects and resolve conflicts, communication within multidisciplinary teams, and productive reflection on their work and the work of others (Alves, Leão, Moreira, & Teixeira, 2018).

2.1.2 | Impact on academic performance

Research on student-centered, project-based engineering education has largely focused on students' overall performance, major retention, and graduation rates (e.g., Al-Holou et al., 1999; Hoit & Ohland, 1998; Knight, Carlson, & Sullivan, 2003). For example, students who took a first-year PBL engineering program had an overall higher third-year GPA, compared with students who were not in the program (Al-Holou et al., 1999). Hoit and Ohland (1998) found that participation in an introductory PBL course, where students rotated in labs from different engineering disciplines, was associated with a 17% increase in retention in engineering by students' third year. Also, a study of a first-year PBL course found that students who took the course were more likely to remain in engineering at the start of their senior year, with greater effects for women, Latino students, and African American students (Knight et al., 2003).

Few studies have examined the impact of PBL on subsequent course learning outcomes. A possible reason for this is PBL targets embedded skills instead of knowledge acquisition, and assessment strategies are, therefore, not as well defined (Hsieh & Knight, 2008). Furthermore, most assessments tend to be cross-sectional rather than longitudinal. Polanco, Calderón, and Delgado (2004) were among the few researchers to follow students who received problem-solving instruction in their second year in the engineering program throughout their college years. Analyses of students' pre- and post-test scores on physics tests, students' GPA, and students' grades in subsequent engineering courses suggested that students who took a course focused on solving engineering problems in their sophomore year performed better in all five subsequent courses than students who attended traditional lectures in their sophomore year. The differences in student performance were statistically significant in two of the five studied courses (Polanco et al., 2004). However, these analyses did not account for potential differences in students' characteristics, namely gender, socioeconomic status, and prior academic preparation. In other words, rigorous empirical research on how PBL experiences early in the engineering program affect students' academic performance in subsequent courses is limited.

2.2 | Diversifying student populations in college engineering

Increasing the diversity in college engineering programs remains a challenge despite institutional efforts to transform instruction and recruit more diverse learners (Olson & Riordan, 2012). This is mirrored in the wide gap between the proportion of underrepresented minorities in science and engineering disciplines and their representation in the U.S. population (NSF, 2017). Although the number of women who earned degrees in engineering has increased over the last two decades from 10,950 Bachelor's degrees awarded in 1995 to 18,626 in 2014, the percentage of total Bachelor's degrees earned by women only increased from 17.3% in 1995 to 19.8% in 2014 (NSF, 2017).

Several factors intertwine and pose challenges for students to thrive in college engineering pathways (Lord et al., 2019). For instance, students whose parents have limited experiences with higher education may experience difficulties in accessing resources for their academic and professional decision-making to navigate engineering programs (Trenor, Yu, Waight, Zerda, & Sha, 2008). Students from lower socioeconomic backgrounds may not have had high-quality K-12 experiences that reinforce their interest in engineering fields prior to college and may lack access to the knowledge of how to request academic support (Syed, Azmitia, & Cooper, 2011). Interactions within the college environment also influence students' engineering pathways. Women and underrepresented minority students reported that role models and peer networks positively influenced their choice to pursue college engineering and persist (Mannon & Schreuders, 2007; Martin, Simmons, & Yu, 2013). However, female students tend to have smaller social networks than their male counterparts (Moore, 1990). Similarly, underrepresented minorities may experience highly competitive peer environments and stigma associated with being a minority in science (Hurtado, Newman, Tran, & Chang, 2010). When subjected to situational cues that present a social identity threat—a threat when people perceive that they may be devalued because of their social identities—women and underrepresented minorities in science reported a lower sense of belonging and less desire to participate compared with male and non-underrepresented minority counterparts (Murphy, Steele, & Gross, 2007; Steele, 1997).

To diversify the college engineering student population, educators have turned to more student-centered pedagogies such as PBL (Chen, Hernandez, & Dong, 2015; Dym et al., 2005; Zastavker, Ong, & Page, 2006). This approach provides students with alternative pathways to reevaluate their learning strategies (i.e., ask and refine questions, collect and analyze data, devise solutions to complex problems; Chen & Chen, 2007). Through these strategy evaluations, students develop cognitive and social skills, namely time and project management, plan revision, communication, and collaboration with peers (Chen & Chen, 2007). Chen et al. (2015) found that students' experiences with their engineering projects were significantly correlated with positive learning outcomes and higher student-reported self-efficacy, or the belief that they can do well in engineering. Although Hispanic students began with lower perceived efficacy than non-Hispanic peers, they reported similar or higher self-efficacy in several areas (e.g., ability to analyze network performance using simulations and knowledge of network simulation) after participating in PBL (Chen et al., 2015). In addition, analyses of course enrollment patterns from a nationally representative survey of students from 121 engineering programs suggest that female students appear to lean toward and persist in disciplines that offer more opportunities for student-focused and collaborative learning approaches (Knight et al., 2012). Collaborative learning could facilitate the acquisition of technical knowledge and mental support for both genders, with women preferring more project work and conversations with project supervisors (Du & Kolmos, 2009).

A note of caution when implementing PBL is that disparities in educational background can result in some students gaining more agency than others in project-based tasks (Crossouard, 2012). Students who were more attuned to traditional lecture approaches may experience frustration when the information to investigate is not readily present in open-ended tasks in PBL (Yadav, Subedi, Lundeberg, & Bunting, 2011). Zastavker et al. (2006) found that male students appeared to enter the engineering program with more technical skills and perceived less anxiety and challenges in project-based coursework, compared with female students. Consequently, it is necessary to scaffold students' learning in PBL, with consideration of its potentially varied impact on different student populations.

Studies that account for students' individual characteristics when examining the impact of PBL in engineering education have mostly centered on students' reported attitudes (Chen et al., 2015; Ro & Knight, 2016). Thus, this study aims to investigate the extent to which a project-based introductory course might influence the subsequent course performance of diverse student subgroups (i.e., first-generation college students, low-income students, females, English language learners, underrepresented minorities, and students with lower academic preparation).

3 | STUDY SETTING

3.1 | Project-based introductory engineering course

This study examined two cohorts (Academic Years 2015–2016, 2016–2017) of students in an elective, introductory, project-based engineering course sequence at a large public research university in Southern California. No students repeated the introductory engineering courses. The course instructors recruited students by presenting a course overview during mandatory first-year student orientations prior to Fall Quarter. Students enrolled in the course for the Fall Term after viewing the course presentation. Students were encouraged to take both terms of this introductory course sequence to satisfy the credit requirements of one technical elective as part of the engineering major graduation requirements. Notably, this is the only introductory engineering course that is offered to first-year students across engineering disciplines. Students self-selected to enroll in this course. Several factors affected the enrollment process, such as student interest in hands-on and PBL, course load of Fall Term, and whether to take an extra course during their first year. Approximately one-third of the first-year student population typically enrolls in the introductory engineering course.

The course design was identical across the two cohorts. The course sequence consisted of weekly 2-hr lectures in Fall, weekly 1-hr lecture in Winter and weekly 2-hr laboratory session over two 10-week terms (Fall and Winter Terms). The purpose of the course is to introduce students to fundamental engineering skills, such as Computer Aided

Design (CAD) modeling and electrical fabrication, as well as concepts such as flight dynamics, fluidic mechanics, electrical circuitry, and control systems, among others. Learning content was embedded in a PBL approach, where formulated PBL skills were explicitly included in the curriculum. Integrating PBL in a first-year engineering course is a common practice among first-year engineering programs (Calabro, Kiger, Lawson, & Zhang, 2008; Knight et al., 2003; Wu, Cassidy, McCarthy, LaRue, & Washington, 2016; Wu, Fischer, Rodriguez, & Washington, 2018). For example, students participated in the product development process through project planning, research, design, manufacturing, and evaluation. In the first term, students focused on designing, building, and testing a remote-controlled quadcopter. Students continued the second term with an autonomous project (autonomous delivery quadcopter, fitness tracker, and a Lab-on-a-Chip concentration detector) that involves sensors, microcontroller, programming, and advanced manufacturing. To mirror real-world aspects of engineering professions, the course invited students to create business plans related to their projects and attend professional talks by industry leaders about trends in engineering research and technology and career pathways. The weekly 2-hr laboratory sessions provided opportunities to design, build, and test the hands-on projects. During the first term, practical engineering skills trainings were provided to students on engineering safety, CAD (SolidWorks), and mechanical and electrical fabrications. During the second term, additional technical instructions were provided on microcontroller programming, electrical circuitry, and sensors. Moreover, students were given the option to integrate advanced manufacturing such as 3D printing and laser cutting as additional fabrication techniques.

A collaborative learning environment was created in both terms. During the first term, students were divided into teams of four to seven using the Comprehensive Assessment of Team Member Effectiveness (CATME) survey based on schedule availability, ethnicity, gender, hands-on skills, and leadership preferences. For example, no female was placed in a group by herself with all males to reduce the possible high anxiety of female students if they started the course with less technical expertise (Zastavker et al., 2006). During the second term, students formed their own teams. As a collaborative learning environment enables students to redevelop their study approaches and develop social skills (Chen & Chen, 2007), students were encouraged to meet at least once a week outside of class. Furthermore, students were required to create a Gantt chart and set milestones to keep the project on schedule and to present weekly progress in front of their peers during the lab session. By mid-term, every team was required to deliver a preliminary design presentation during lab and receive feedback from peers and the lab instructor. Extra open lab hours were offered to students to provide additional time necessary for students to complete the project in groups.

3.2 | Subsequent engineering courses

This study generated a list of subsequent courses that students in the project-based introductory engineering course took based on institutional data of all students who took engineering courses between 2015 and 2017. The criteria for selecting a course for analysis were as follows: (a) to achieve enough statistical power for analyses, the course included more than 40 students who took the project-based introductory engineering course (so that the overall sample size of each subsequent course was at least 80 for balanced samples) and (b) students took the subsequent courses for grades and not for credits only (as pass/no pass) to maintain consistency for the outcome variable (i.e., course grades). The courses that met the selection criteria were offered in Spring 2016 and 2017, the term immediately following the introductory engineering sequence, or in Fall 2016 and 2017, approximately six to eight months after the introductory engineering sequence. Analyses included only the first attempt for students who took the courses twice. Instructors of the introductory project-based course did not teach any of the subsequent courses. Descriptions of the subsequent engineering courses that met the selection criteria are given in the following. To the best of our knowledge, the subsequent courses do not include PBL components.

3.2.1 | Introduction to engineering computations

This course is required for students majoring in mechanical engineering, aerospace engineering and materials science engineering. Course objectives include introduction to solutions of engineering problems through the use of computers (e.g., application of software flow control, modular programming, and single- and multi-dimensional arrays). The course meets every week for one 3-hr lecture and a 1-hr discussion session. Homework assignments are implemented as engineering design problem sets.

3.2.2 | Introduction to electrical engineering and computer engineering

This course is required for students majoring in electrical engineering and computer engineering. The course aims to introduce students to the subdisciplines of electrical engineering, namely Electronic Circuit Design, Semiconductors and Optoelectronics, and Digital Signal Processing, as well as present an overview of computer programming, software and hardware systems, and chip design. The course meets for 1 hr of lecture per week.

3.2.3 | Statics

This course is required for students majoring in civil engineering, environmental engineering, mechanical engineering, aerospace engineering, and materials science engineering. Examples of learning outcomes include use of theory and methods to analyze simple trusses, formulation of static problems for structural beams, and calculation of area centroids. The course consists of a 3-hr lecture and a 1-hr discussion each week.

3.2.4 | Introduction to digital systems

This course is required for students majoring in electrical engineering, computer engineering and computer science engineering. Students who complete the course will be able to manipulate or design information processing and number presentation in binary form. Students will also be able to design basic operators and circuits. The course meets every week for 3 hr of lecture and 1 hr of discussion.

3.2.5 | Advanced C programming

This course is required for students majoring in computer engineering. Upon completing the course, students will be able to understand language programming concepts in C and design and implement dynamic data structures using user-defined data types. The weekly schedule of the course consists of 3 hr of lecture and 2 hr of discussion sessions.

4 | RESEARCH QUESTIONS

This study contributes to the research base on the impact of enrolling in a project-based introductory engineering course on students' success in subsequent engineering courses. In addition, this study examines heterogeneity effects of participation in the project-based introductory engineering course for diverse student populations. The research questions are as follows:

1. How do student characteristics relate to their enrollment in the project-based introductory engineering course?
2. What are the associations of participation in the project-based introductory engineering course on student performance in subsequent engineering courses?
3. What are the associations of participation in the project-based introductory engineering course on student performance in subsequent engineering courses for diverse student populations (i.e., first-generation college students, low-income students, females, English language learners, underrepresented minorities, and students with lower academic preparation)?

Drawing on prior work on the impacts of PBL (Chen et al., 2015; Mills & Treagust, 2003; Polanco et al., 2004), this study hypothesized (a) that participation in the introductory PBL engineering course would be correlated with higher academic performance in subsequent engineering courses and (b) that diverse student populations would mostly benefit from PBL course enrollment. However, students with weaker educational preparedness would benefit less from PBL course enrollment.

5 | METHOD

5.1 | Data sources and sample

This study was conducted at a large public research university in Southern California, and it is connected to two large projects funded by the National Science Foundation. Data were provided from a number of sources, namely the Registrar's Office, the Office of Institutional Research, the Office of Information Technology, Admissions, and the Office of Financial Aid and Scholarships. Table 1 provides descriptive statistics of the full sample (n = 1,318), which consists of students who were enrolled in at least one of the following five subsequent engineering courses: (1) Introduction to Engineering Computations, (2) Introduction to Electrical Engineering and Computer Engineering, (3) Statics, (4) Introduction to Digital Systems, and (5) Advanced C Programming.

The study particularly focuses on students who completed both terms of the project-based introductory engineering course (Fall 2015–Winter 2016 or Fall 2016–Winter 2017; see Table 2 for descriptive statistics). As the content, assignment, and instructors of the project-based introductory engineering course was identical and the student demographics were sufficiently similar across cohorts, we collapsed data across these two cohorts for the analyses (and included a control variable for cohorts to control for potential unobserved biases). Overall, the two cohorts were culturally diverse (49.6% are Latino or Hispanic, American Indian, Black or African American, Alaska Native, or Pacific Islander) and largely consisted of male students (82.2%). Approximately 34.4% of students were classified as low-income based on household income and size at the 185% U.S. poverty line cutoff. About 41.3% of students were first-generation college students (i.e., neither of their parents holds a Bachelor's degree), and 31.5% were English language learners (i.e., language other than English is the student's first language). The demographic patterns mirror those in the national sample of students aspiring to major in engineering in terms of gender but were more diverse (the national sample

TABLE 1 Descriptive statistics of full sample (n = 1,318)

	Full sample (n = 1,318)		Took intro Engr (n = 259)		Did not take intro Engr (n = 1,059)		
	M, %	*SD*	*M*, %	*SD*	*M*, %	*SD*	% Missing
Demographics							
First-generation	40.67	–	41.31	–	40.51	–	2.80
Low-income	34.45	–	34.36	–	34.47	–	0.00
English language learner	41.32	–	31.50	–	43.72	–	0.00
Underrepresented minority	54.72	–	49.58	–	55.98	–	0.00
Female	21.25	–	17.76	–	22.10	–	0.45
Academic readiness							
Admissions score	239.44	20.09	245.27	19.52	238.76	19.64	8.04
High school GPA	3.96	.25	4.06	.18	3.94	.25	0.00
Number of engineering courses[a]	2.31	2.43	3.51	1.66	2.02	2.58	0.00
Year taking subsequent courses							0.00
2015–2016	51.93	–	27.80	–	57.83	–	
2016–2017	48.07	–	72.20	–	42.17	–	

Course grades	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*	*n*	% missing
Intro to Engineering Computations	2.55	1.01	316	2.66	.99	124	2.52	1.02	192	0.00
Intro to Electrical Engineering	3.81	.60	466	3.91	.40	133	3.78	.65	333	0.00
Statics	2.58	1.11	569	2.65	.88	91	2.57	1.14	478	0.00
Intro to Digital Systems	2.94	.99	147	2.81	1.05	49	3.00	.97	98	0.00
Advanced C Programming	2.93	1.32	147	2.98	1.35	68	2.91	1.31	79	0.00

Abbreviation: *M*, mean.

[a]Number of courses taken in the two terms that introductory engineering was offered, including the introductory engineering courses.

TABLE 2 Descriptive statistics of students who enrolled in the project-based introductory engineering course

	Both cohorts (n = 259)		Cohort 15–16 (n = 88)		Cohort 16–17 (n = 171)	
	Mean, %	***SD***	**Mean, %**	***SD***	**Mean, %**	***SD***
Student demographics						
First-generation	41.31	–	49.82	–	47.28	–
Low-income	34.36	–	40.91	–	30.99	–
English language learner	31.50	–	30.68	–	26.32	–
Underrepresented minority	49.58	–	48.38	–	50.10	–
Female	17.76	–	17.05	–	18.13	–
Academic readiness						
Admissions score	245.27	19.52	243.96	19.36	248.09	19.77
High school GPA	4.06	.18	4.08	0.16	4.04	0.19
Number of engineering courses[a]	3.51	1.66	3.54	1.54	3.49	1.72
Year taking subsequent course						
2015–2016	27.80	–	81.82	–	0	–
2016–2017	72.20	–	18.18	–	100	–

[a]Number of courses taken in the two terms that introductory engineering was offered, including the introductory engineering courses.

included 25.2% students whose family income was below \$50,000, 23.3% students whose mother had no college degree, and 28.8% underrepresented minority students; Eagan, Hurtado, Figueroa, & Hughes, 2014).

As a robustness check, logistic regression analyses with robust standard errors were conducted to examine potential survivor biases. Analyses examined whether the student populations in this study (students who were enrolled in the School of Engineering at the beginning of their first year and remained in the school by the end of their second year) were different compared with students who left engineering by their second year. Varying attrition rates for different populations would limit our ability to draw conclusions about those populations. Results indicated that the students who stayed and were included in this study (i.e., "stayer," n = 1,318) did not differ from those who left engineering (i.e., "leaver," n = 255) in terms of demographics (i.e., URM, first generation, gender, low income, English language learners) and across cohorts (i.e., 2015 or 2016). However, stayers had significantly higher high school GPA ($OR = 1.29$, $SE = 1.07$, $z = 3.70$, $p < .001$) and admissions score (odds ratio; $OR = 1.22$, $SE = 1.07$, $z = 2.58$, $p < .05$) compared with leavers. Propensity score matching approaches were utilized in later analyses to alleviate biases (e.g., survivor biases, sample biases) from unobserved and potentially confounding variables (Austin & Platt, 2010).

5.2 | Measures

5.2.1 | Dependent variable

The dependent variable in Research Question 1 indicates whether students enrolled in the project-based introductory engineering course (0: no enrollment; 1: enrollment). The dependent variable in Research Questions 2 and 3 describes student grades in the subsequent engineering courses (F = 0.0, D− = 0.7, D = 1.0, D+ = 1.3,..., B = 3.0, B+ = 3.3, A− = 3.7, A = 4.0, A+ = 4.0).

5.2.2 | Independent variables

The independent variables in Research Question 1 function as covariates in Research Questions 2 and 3. The independent variable in Research Questions 2 and 3 indicates students' participation in the project-based introductory engineering course (0: no enrollment; 1: enrollment). Students who took the project-based introductory engineering course were classified as the treatment group, and those who did not were classified as the comparison group. Covariates for Research Questions 2 and 3 (and independent variables for Research Question 1) include dichotomous variables for *students' demographics*: female (0: male; 1: female), low-income status (0: not tagged as low-income based on family household income and household size; 1: tagged as low-income at the 185% U.S. poverty line cutoff), first-generation college student (0: at least one parent holds a Bachelor's degree or higher; 1: neither parent holds a Bachelor's degree), English language learner (0: English or English and another language is student's first language; 1: language other than English is student's first language), and racial/ethnic underrepresented minority status (URM; 0: White or Asian or Asian American; 1: Latino or Hispanic, American Indian, Black or African American, Alaska Native, or Pacific Islander). To account for *students' academic preparation*, variables included students' high school grade point average, number of engineering courses students took in the two quarters the project-based introductory engineering course sequence was offered (including the introductory engineering courses), year taking subsequent course, and students' admissions score (i.e., a composite admissions score based on students' ACT/SAT performance). A 100 in admissions score is equivalent to an 800 in SAT and a 36 in ACT subject tests. Total admissions score (scale of 60–300) account for students' best scores in SAT critical reading, math, and writing in a single sitting and two subject tests from different fields, or ACT math, reading, science, and combined English (for details of how the university scores are calculated, see UC Admission, n.d.). The continuous variables (admissions score and high school GPA) were z-score transformed. In addition, a dummy year variable when the course was offered (0: 2015–2016; 1: 2016–2017) was included to account for potential unobserved differences across years. Descriptive statistics for each variable are listed in Table 1.

5.3 | Analytical methods

5.3.1 | Research Question 1

Logistic regression analyses with robust standard errors were conducted to answer the first research question about students' probability to enroll in the project-based introductory engineering course (Harrell, 2015). The analysis sample included all students in the five subsequent engineering courses. The study reports average marginal effects (AMEs). AMEs represent the average change in the probability to enroll in the project-based introductory engineering course for each unit increase in an independent variable.

Assumptions of logistic regression models were met. For instance, a Wald test for the model was conducted to check the linearity of independent continuous variables and log odds and found that the explanatory variables were significant ($p < .01$). These results indicate that the coefficients for the independent variables are not simultaneously equal to zero, and, thus, the inclusion of these variables results in a statistically significant improvement in model fit. Also, variance inflation factors (VIFs) were computed to check multicollinearity. VIF results ranged between 1.01 and 1.30, indicating the absence of high collinearity among variables (Hair Jr., Anderson, Tatham, & Black, 1995).

5.3.2 | Research Question 2

The analysis investigated the impact of completing the engineering course sequence through a "doubly robust" propensity score matching approach. Propensity scores are probability estimates of subjects in the treatment condition accounting for potential confounding variables. Propensity score matching methods have been used to reduce sample biases in non-experimental settings with existing systematic differences between the treatment and comparison groups (Dehejia & Wahba, 2002). The current study uses the propensity scores as inverse probabilities of treatment weights for the regression models (Austin, 2011). The variables included in the propensity score models include demographic characteristics that prior research has found to be associated with academic outcomes (e.g., Lord et al., 2019). The selection of these variables follows the recommendations of Brookhart et al. (2006) and Rubin and Thomas (1996) that propensity score models should include variables related to outcome (i.e., academic performance), regardless of their relation to treatment (i.e., course enrollment). The weighting approach was chosen instead of matching of propensity scores to minimize reduction in sample size and reduce bias in estimating treatment effects (i.e., by giving more weight to individuals with closer propensity scores; Hirano, Imbens, & Ridder, 2003). The method provides more robust estimates compared with ordinary least squares regression analysis that does not account for selection biases from confounding variables (Hirano et al., 2003).

This study applied inverse-probability weights with regression adjustment for multiple linear models to estimate the average treatment effect on the treated (ATT) of participating in the project-based introductory engineering course on student performance in subsequent engineering courses (Greifer, 2019a; Greifer, 2019b). ATT refers to the treatment effect that is averaged across all observations in the treatment condition. Inverse-probability weights with regression adjustment were applied on the sample of all students separately for each of the five subsequent courses. Notably, this study reports on the ATT and their 95% confidence interval as well as significance levels. ATT can be viewed as an effect size estimation with 0.3 representing a letter grade difference, for instance, C+ (i.e., 2.4) compared with a B– (i.e., 2.7) or B (i.e., 3.0) compared with a B+ (i.e., 3.3).

5.3.3 | Research Question 3

The same method as Research Question 2 (multiple regression with inverse-probability weights) was applied to determine possible heterogeneity effects of treatment based on student background variables (Greifer, 2019a, Greifer, 2019b). We created subsets from the full sample based on these background variables, namely low-income status, gender, first-generation college status, English language learner status, underrepresented minority status, and academic preparedness level, to perform analyses. For academic preparedness, students were segmented into three groups based on their admissions score quartile: bottom 25%, 25–75%, and top 25%.

Before analyses for Research Questions 2 and 3 were conducted, balance across treatment and comparison groups after propensity score matching was examined. The model-adjusted differences in means between treatment and control group were all below 0.05. In addition, the variance ratio adjustment results ranged between 1.03 and 1.10. Both statistics suggested that covariates were balanced across treatment and control groups in the propensity score weighted samples.

Although propensity score weighting can adjust for observed features, it may not account for the unmeasured biases that are correlated with both the treatment (the probability to have taken the project-based introductory engineering course) and the outcomes (course grades). Sensitivity analyses were conducted after each model in Research Questions 2 and 3 to assess how sensitive the treatment estimates are to unobserved factors (i.e., hidden bias w). As suggested by Ridgeway, McCaffrey, Morral, Burgette, & Griffin (2017), this study conducted sensitivity analyses by choosing alternate values for the ratio between the predicted propensity score weight and the weight when a hidden bias exists [a = w(xi, zi)/w(xi)] as well as the correlation between the ratio and the outcome (ai, yi). The analyses calculated the "break even correlation," the smallest correlation between the outcome variable and the unobserved bias for which our conclusion of a treatment effect becomes invalid (for a detailed explanation of the method, see Ridgeway et al. (2017)).

Possible degradation of thresholds was addressed following the Benjamini–Hochberg procedure (Benjamini & Hochberg, 1995). Analyses of the full and subsamples were based on separate subgroups and, therefore, met the assumptions of independent tests. We set the false discovery rate at .05 and found that the tests for the treatment variable were significant with individual p-values smaller than the Benjamini–Hochberg critical value.

All analyses were conducted in R 3.4.3 (R Core Team, 2017). Analyses used listwise deletion of missing cases upon inspection of missing data patterns. Kruskal–Wallis tests and Chi-squared tests indicate no significant difference between missing and observed data for students who took the first-year course and those who did not. This study utilized the following packages: data pre-processing and analyses ("dplyr," Wickham, François, Henry, & Müller, 2018; "psych," Revelle, 2018; "survey," Lumley, 2004; "VIM," Kowarik & Templ, 2016), propensity score matching and estimates of average treatment effects ("WeightIt," Greifer, 2019a), sensitivity analyses ("twang," Ridgeway et al., 2017), checking balance in weighted samples ("cobalt," Greifer, 2019b), and plotting ("ggplot2," Wickham, 2016; "ggpubr," Kassambara, 2018).

6 | RESULTS

6.1 | Examining characteristics related to enrollment in the project-based introductory engineering course

Findings from the logistic regression model with robust standard errors suggest that some student characteristics predicted enrollment in the project-based introductory engineering course (Table 3). In general, among students who took subsequent engineering courses, low-income status, first-generation college status, and underrepresented minority

TABLE 3 Logistic regression model with robust standard errors predicting enrollment in project-based introductory engineering course

	Odds ratio	AME	z	p
Intercept	1.35			<.001***
First-generation	1.03	0.02	1.00	.32
Low-income	1.01	0.01	0.42	.67
English language learner	0.95	−0.05	−1.48	.02*
Underrepresented minority	1.04	0.04	1.62	.11
Female	0.96	−0.04	−1.48	.01*
Admissions score	1.07	0.07	4.70	<.001***
Number of engineering courses[a]	1.04	0.03	4.23	<.001***
Year taking subsequent course	1.09	0.08	3.88	<.001***
High school GPA	1.12	0.12	6.31	<.001***

Abbreviation: AME, average marginal effect.
[a]Number of courses taken in the two terms that introductory engineering was offered, including the introductory engineering courses.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

status were not significantly associated with student enrollment in the project-based introductory engineering course. The probability of female students to enroll in the project-based introductory engineering course was 4% lower compared with male students (AME $= -0.04$, $z = -1.48$, $p < .05$). Also, the probability of English language learners to be enrolled in the project-based introductory engineering course was 5% lower compared with non-English language learner students (AME $= -0.05$, $z = -1.48$, $p < .05$). Notably, results reveal that academic readiness was significantly associated with students' decision to participate in the introductory engineering course. On average, a one *SD* increase in students' admissions scores increased the probability of enrollment in the project-based introductory engineering course by 7% (AME $= 0.07$, $z = 4.70$, $p < .001$). Similarly, a one-standard-deviation increase in students' high school GPA increased the probability of enrollment in the project-based introductory engineering course by 12% (AME $= .12$, $z = 6.31$, $p < .001$). In addition, each additional engineering course that students enrolled in during the terms in which the project-based introductory engineering course was offered increased the probability of their enrollment in the project-based introductory engineering course by 3% (AME $= .03$, $z = 4.23$, $p < .001$).

6.2 | Examining subsequent course grades

This study utilized inverse-probability weights with regression adjustment and robust standard errors to estimate the average treatment effect of enrollment in the project-based introductory engineering course on subsequent course grades (Table 4). Overall, we found a statistically significant, positive association between enrollment in the project-based introductory engineering course and students' performance in two of the five subsequent engineering courses. On average, relative to those who did not take the project-based introductory engineering course, students who did take it performed approximately a letter grade better in the Introduction to Engineering Computations course, average treatment effect on the treated: ATT $= .31$, $SE = .14$, $p < .05$. This means that taking the project-based introductory engineering course could improve one's grade in this subsequent course from a C+ (i.e., 2.4) to a B− (i.e., 2.7) or from a B (i.e., 3.0) to a B+ (i.e., 3.3). Findings also indicated an average treatment effect on the treated of about half a letter grade in the Introduction to Electrical Engineering and Computer Engineering course for students who took the project-based introductory engineering course, ATT $= .13$, $SE = .05$, $p = .01$.

6.3 | Examining influence for diverse student populations

Regression models using inverse-probability weights and robust standard errors were conducted for several student subgroups to examine associations of enrollment in the project-based introductory engineering course with subsequent engineering course grades (Figure 1).

TABLE 4 Average treatment effects on the treated (ATT) of enrollment in project-based introductory engineering course using inverse-probability weights with regression adjustment

Subsequent course (grades)	*n*	ATT	95% CI	*SE*	*p*
Intro to engineering computations	316	0.31	[0.03, 0.58]	0.14	.03*
Intro to electrical engineering	466	0.13	[0.03, 0.24]	0.05	.01*
Statics	569	0.08	[−0.14, 0.29]	0.11	.49
Intro to digital systems	147	−0.19	[−0.59, 0.21]	0.20	.36
Advanced C programming	147	0.14	[−0.36, 0.64]	0.26	.58

Note: Variables used to generate weights and covariates for the model include students' demographics (i.e., first-generation college student status, low-income status, English language learner status, gender, and underrepresented minority status) as well as students' academic preparation (i.e., high school GPA, admissions scores, year students took the subsequent course, number of engineering courses taken in the two terms that introductory engineering was offered, including the introductory engineering courses).
Abbreviations: ATT, average treatment effect on the treated; 95% CI, 95% confidence interval; *SE*, standard error.
*$p < .05$.

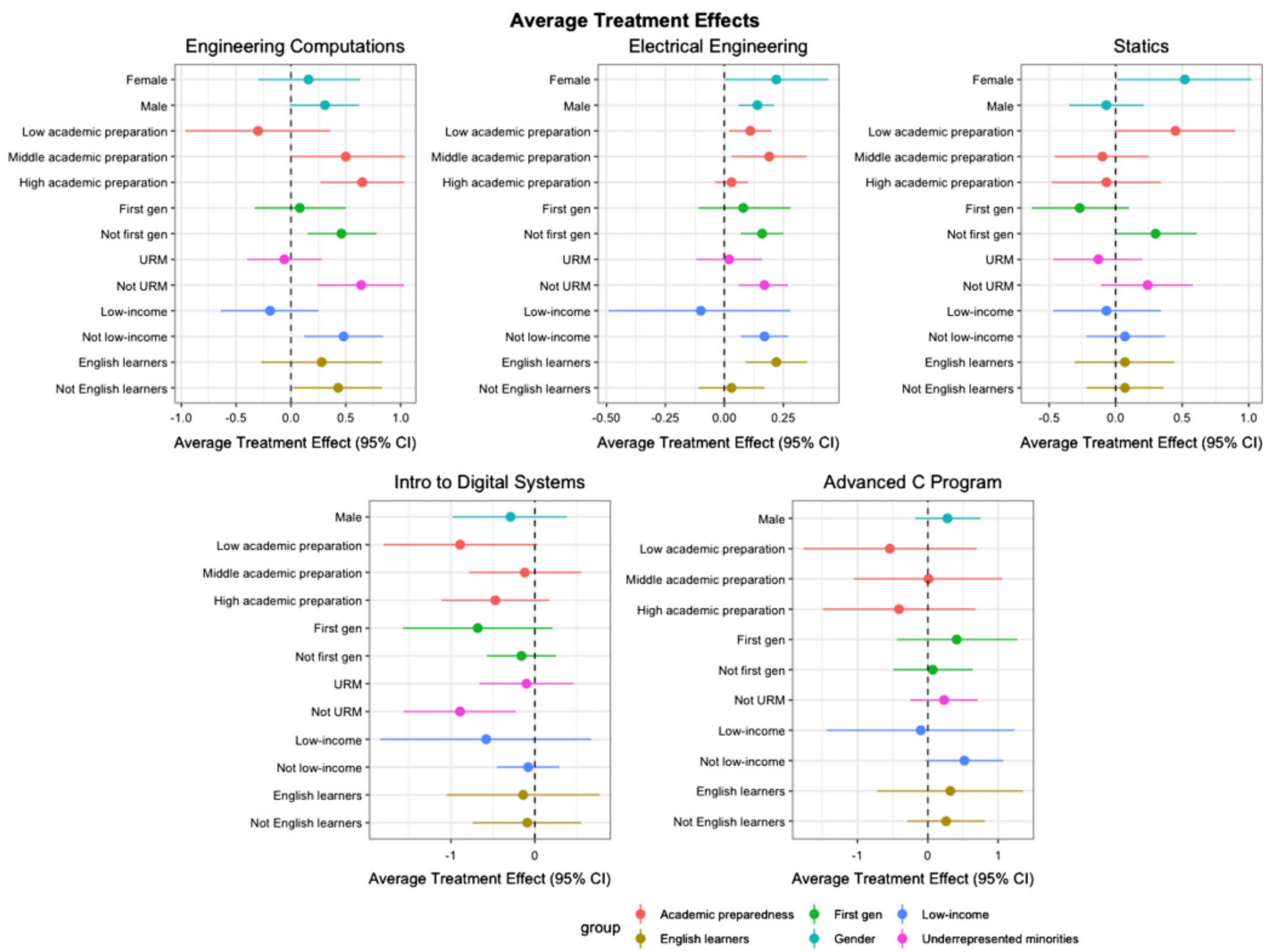

FIGURE 1 Average treatment effect for subgroups of students in engineering classes, using inverse-probability weights from propensity scores in regression adjustments. Error bars represent the 95% confidence interval. URM, underrepresented minority students. Academic preparation was calculated based on admissions score's lowest 25%, 25–75%, and top 25%. Certain groups excluded from analyses due to small sample size [Color figure can be viewed at wileyonlinelibrary.com]

Overall, female students who took the project-based introductory engineering courses performed significantly better in Introduction to Electrical Engineering and Computer Engineering and Statics compared with female students who did not participate in the project-based introductory engineering course, ATT = .22, *SE* = .11, $p < .05$ and ATT = .52, *SE* = .25, $p < .05$, respectively. In addition, English language learners who took the project-based introductory engineering course performed significantly better in the Introduction to Electrical Engineering and Computer Engineering course compared with English language learners who did not participate in the project-based introductory engineering course sequence, ATT = .22, *SE* = .07, $p < .001$.

Subgroup analyses based on students' admissions scores suggest that students at different levels of academic readiness might benefit from taking the project-based introductory engineering course. For students who were less academically prepared (i.e., bottom 25% of admissions scores), participating in the project-based introductory engineering course was associated with a higher course grade in two courses, Introduction to Electrical Engineering and Computer Engineering (ATT = .11, *SE* = .04, $p < .01$) and Statics (ATT = .45, *SE* = .23, $p < .05$) compared with not participating in the project-based introductory engineering course. Participation in the project-based introductory engineering course was significantly associated with subsequent course performance for students with medium academic preparedness (i.e., 25–75% of admissions scores) in Introduction to Engineering Computations (ATT = .50, *SE* = .26, $p < .05$) and Introduction to Electrical Engineering and Computer Engineering (ATT = .19, *SE* = .08, $p < .05$) compared with students with similar academic preparedness who did not participate in the project-based introductory engineering course.

Results from the Introduction to Engineering Computations course revealed heterogeneity effects of participating in the project-based introductory engineering course among student subpopulations. Students who are traditionally successful in engineering education tend to realize larger benefits from participating in the introductory engineering course. For example, non-URM students who enrolled in the project-based introductory engineering course performed about two letter grades better in Introduction to Engineering Computations compared with non-URM students who did not take the project-based introductory engineering course, ATT = 0.64, *SE* = 0.20, $p < .001$. This pattern is similar for students who were not first-generation college students, ATT = 0.46, *SE* = 0.16, $p < .001$; not low-income, ATT = 0.48; *SE* = 0.18, $p < .001$; and not English language learners, ATT = 0.43, *SE* = 0.20, $p < .05$, who were enrolled in the project-based introductory engineering course compared with their counterparts who did not take the project-based introductory engineering course. Similarly, male students who were enrolled in the project-based introductory engineering course performed about a letter grade better in Introduction to Engineering Computations compared with other males who were not enrolled in the project-based introductory engineering course, ATT = 0.31, *SE* = 0.16, $p = .05$. Similar differences in performance across underrepresented and non-underrepresented student groups were also present in the Introduction to Electrical Engineering and Computer Engineering course.

7 | DISCUSSION

This study examines the association between students' participation in the project-based introductory engineering course and their performance in subsequent engineering courses. The study responds to the need for studies that examine promising courses with the goal of supporting student success in engineering majors. In addition, it advances the growing research base on the benefits of PBL in introductory courses on students' subsequent engineering courses with a particular focus on different student populations. The four main findings of this study are discussed in light of their implications for educational stakeholders in engineering programs.

First, enrollment in the project-based introductory engineering course did not substantially differ by student demographics. However, students enrolled in the project-based introductory engineering course were on average more academically prepared. This finding has implications for engineering faculty to promote project-based introductory engineering courses. For instance, engineering departments could frame the course as an exploratory learning experience with ample opportunities for peer support, disseminate flyers to academic counselors, and facilitate presentations in undergraduate courses led by role models—peers who took and benefited from the introductory course. A shift in emphasis from taking a course as a requirement to an exploration of engineering topics has been found to be positively related to student motivation (Klingbeil & Bourne, 2015).

Second, participation in a project-based introductory engineering course is associated with higher student performance in subsequent engineering courses. These findings echo research that indicates the beneficial effects of PBL in engineering (Fernandes, Mesquita, Flores, & Lima, 2014). In particular, PBL may enhance students' ability to communicate in teams and to monitor and adjust their own progress in student-directed learning (Frank, Lavy, & Elata, 2003). When incorporated across courses throughout undergraduate study, PBL appears to enhance students' ability to apply knowledge to solving real-world problems collaboratively (Litzinger, Lattuca, Hadgraft, & Newstetter, 2011). The application of engineering principles to real-world issues was observed in the association between PBL and higher student performance in specific subsequent courses in this study. For example, although not employing collaborative PBL or active learning approaches, the Introduction to Engineering Computations course requires students to solve engineering design problem sets and applies their knowledge to real-life contexts. Engineering departments should feel encouraged to offer courses that integrate PBL elements for students early on in their undergraduate program to lay the foundation for later engineering courses.

Third, female students who participated in the project-based introductory engineering course had associations with higher performance in more advanced engineering courses. This is a promising finding as female students traditionally account for a low proportion of engineering majors (Allen-Ramdial & Campbell, 2014; Olson & Riordan, 2012). To better support female students, instructors of engineering courses may embed elements of PBL into their course materials. This finding mirrors prior research that female students tend to gravitate toward courses that offer student-focused and collaborative learning approaches (Knight et al., 2012).

Fourth, students who are traditionally successful in engineering education tend to realize more benefits from participating in the project-based introductory engineering course. Notably, participation in the project-based introductory engineering course for their underrepresented counterparts (i.e., low-income students, first-generation students, URM students, students with weaker academic preparation) was not negatively associated with performance in subsequent courses compared with students who did not participate in the project-based introductory engineering course. Nonetheless, these findings correspond to prior work, which indicates that student-directed learning can result in different learning gains among students from different socioeconomic backgrounds and with different academic preparedness (Crossouard, 2012). Despite not disadvantaging students in the courses studied, it remains important to explore ways to support instruction to equitably benefit all students. Approaches to more equitably advance student competence in knowledge and skills acquired through project-based engineering include the two-phase process suggested by Kokotsaki, Menzies, and Wiggins (2016). In this approach, students first develop knowledge of technical concepts and procedures through activities that are accessible across the academic preparedness range before transitioning to designing their own projects (Kokotsaki et al., 2016). Additionally, learning activities and assessment may focus on the quality of group processes, particularly equal participation and interdependence among group members, to foster learning equity for all students (Crossouard, 2012).

Overall, findings from this study indicate that project-based introductory engineering courses can support students on their path through engineering majors. In particular, courses that include PBL can benefit undergraduate students overall, and female students in particular. This might contribute to increasing the overall persistence and graduation rates of women in undergraduate engineering programs, ultimately providing a promising path for engineering departments to broaden pathways to engineering.

7.1 | Limitations

Several limitations should be considered when interpreting the findings and implications of this study. First, data from this study are collected from a large, selective public research university that served a significantly higher number of Asian and first-generation college students. Notably, gender-based demographic patterns mirror those in a national sample of students aspiring to major in engineering (predominantly male students; Eagan et al., 2014). Following Pawley's (2017) advice to specify whether the study sample is representative of the engineering population, we acknowledge that findings may not be generalizable across other contexts.

Second, the small sample sizes of some student subgroups within each subsequent course resulted in fairly large standard errors of the ATT estimates. In addition, several subsequent engineering courses at this university did not meet the sample size inclusion criteria in this study.

Third, the project-based course examined is an elective not directly tied to other courses in the first-year curriculum nor serves as a prerequisite for subsequent courses. Thus, we did not explore how the project-based component influenced specific knowledge and practice components in subsequent courses.

Fourth, this study examined only institutional variables. Psychological constructs such as student motivation, self-efficacy beliefs, and interests in engineering, among others, may be valuable in predicting students' course enrollment and performance but were impossible to collect at scale and, therefore, not included in analyses. This study performed sensitivity analyses to evaluate potential hidden biases that would invalidate the treatment effects observed. Results from these analyses suggested that it is unlikely that there are unobserved variables that would invalidate the treatment effects of the full-group analysis. If such factors existed, they will have to be moderately to largely correlated with the course grades after controlling for all the regression covariates as indicated through breakeven correlation coefficients (Ridgeway et al., 2017). However, sensitivity analyses examining heterogeneity effects indicated that the treatment effects observed from some student subgroups may be more sensitive to hidden biases. For instance, the analysis of the low-income subgroup in the Introduction to Engineering Computations course indicates that unobserved factors likely exist that affect students' probability to enroll in the project-based introductory engineering course, which are weakly correlated with students' final course grades (correlation coefficient <.06). Thus, treatment effect estimates for this subgroup may be less robust.

7.2 | Future work

This study motivates future research in several directions. First, the study design could be replicated with different student demographics from other institutions, including community colleges, liberal arts institutions, and private universities to validate the generalizability of the findings. Second, future studies may extend the current focus of examining student success in subsequent engineering courses within a year following participation in the project-based introductory engineering course to even more distant student success indicators such as major retention, time-to-degree, and graduation rates. Third, future research may explore different iterations of the introductory course with different engineering designs and practices. Such studies may allow us to understand the potential impacts of PBL on students' subsequent performance in subsequent courses that employed similar or different concepts and practices. Fourth, follow-up analysis could use an in-depth case study approach that follows a purposeful sample of students to examine the underlying mechanisms through which project- and problem-based learning may support long-term academic performance. Finally, future research could develop and evaluate the design and implementation of instructional interventions that attempt to promote learning opportunities for students traditionally underrepresented in engineering education to further support educational equity in engineering.

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