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RESEARCH ARTICLE

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The multiplicative function of expectancy and value in predicting engineering students' choice, persistence, and performance

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Abstract

Background: Students are more likely to persist when they both perceive themselves as capable of success (expectancy) and perceive tasks to be interesting, important, and useful (values) or less costly in terms of effort, lost opportunities, and psychological stress (perceived costs). Prior research has not examined whether these motivational beliefs synergistically predict engineering-related outcomes; studying such synergy is critical for understanding how multiple forms of motivation combine to support engineering persistence.

Purpose/Hypothesis: We tested how engineering academic self-efficacy (expectancy), values/costs, and their interaction predicted engineering-related outcomes. We hypothesized that there would be significant interactions between self-efficacy and values/costs in predicting engineering persistence and academic success.

Design/Method: Structural equation modeling was used to investigate latent interactions between self-efficacy and values/costs (interest, attainment, and utility values; opportunity, effort, and psychological costs) in predicting career intentions, aspirations for engineering graduate school, and engineering retention, and grades in foundational courses for engineering among first-year engineering undergraduates ($n = 2420$).

Results: Significant interactions between self-efficacy and values (interest and utility only) were identified, but not for self-efficacy and attainment value or costs. Feeling both competent in engineering and highly valuing engineering were simultaneously related to higher engineering persistence, as compared to either feeling competent or valuing engineering alone.

Conclusions: The findings contribute to expectancy–value theory by providing a more precise understanding of the role of each type of value and cost in predicting distal outcomes, and practicing by highlighting the importance of supporting both expectancy and values when intervening to support engineering persistence.

KEYWORDS
expectancy–value theory, latent interaction, motivation, perceived costs, persistence

1 | INTRODUCTION

Workforce needs in the United States, particularly the anticipated deficit of college engineering graduates in the next decade (Sargent, 2017), indicate that it is critical to understand how and why some students choose to persist in pursuing engineering, but others do not. Research has documented that, on average, academic motivation decreases over time (Fredricks & Eccles, 2002). Declining motivation in science, technology, engineering, and mathematics (STEM) during college is not an exception (Robinson et al., 2018). Yet, motivation is an essential ingredient explaining students' success and persistence in engineering; in particular, interest appears to be a major factor in STEM persistence (Seymour & Hewitt, 1997).

Importantly, a single form of motivation may not sufficiently explain differences in engineering persistence (Matusovich et al., 2010; Wu et al., 2020). Students may need to feel both capable of (expectancy) and interested in (values) engineering-related tasks for successful performance in engineering (Atkinson, 1957; Eccles, 1983). For example, engineering college students who feel highly efficacious at engineering work may not necessarily persist in earning an engineering degree if they do not perceive engineering as interesting. To understand student success, we must consider how expectancy and values work together synergistically.

To this end, research has begun to examine the interaction effects of expectancy and values on students' choice and performance (Nagengast et al., 2011; Trautwein et al., 2012). This research suggests that having high expectancy *and* values at the same time yields more benefits than the independent effect of either high expectancy *or* high values. While prior research has documented the importance of expectancy and values in explaining engineering motivation and outcomes (Brown et al., 2015), to our knowledge, no research has examined the interaction between expectancy and values among engineering students.

Expectancy and values are domain-specific (Wigfield & Eccles, 2000), and motivation may function differently in engineering than other domains (e.g., English, science in general). For instance, people may have different conceptualizations of competence in fields, such as engineering, that rely more on mathematics (e.g., brilliance viewed as necessary for success in STEM-related fields; Leslie et al., 2015) and often perceive engineering as costly in terms of their effort, stress, and/or the need to give up other valued pursuits due to heavy courseloads and strict grading policies (Seymour & Hewitt, 1997). Given these potential differences in how competence is characterized within engineering and the unique demands of studying engineering in college, it is critical to examine how expectancy and values function synergistically among engineering undergraduates specifically. Thus, the current study investigates how expectancy and values/costs combine to predict key outcomes. This research is critical for understanding the psychological mechanisms that help to support engineering persistence, which helps inform the types of educational interventions that might be most useful for undergraduate engineering programs.

2 | THEORETICAL BACKGROUND

2.1 | Expectancy, values, and costs

The situated expectancy–value theory posits that expectancies for success and task values play key roles in individuals' choices, persistence, and performance (Eccles, 1983; Eccles & Wigfield, 2020). *Expectancy* refers to beliefs about how one will perform on a future task, and *task values* refer to students' reasons for doing an activity (Wigfield & Eccles, 2000), including *interest* value (enjoyment one derives from performing a task), *attainment* value (perceived importance of a task to one's identity), *utility* value (perceived usefulness of a task for one's current or future goals), and perceived *costs* (perceived negative consequences associated with engaging in a task). Although the first three task values generally positively predict achievement-related outcomes, they are conceptually and empirically differentiated from one another and show unique relations to correlates (Gaspard et al., 2015).

Research shows that expectancy and values uniquely predict a variety of observed and self-reported outcomes of interest to educators and policymakers, including academic performance (e.g., school grades), career- and educational-related choice, and persistence (e.g., intentions, aspirations, retention). In general, expectancy is a stronger predictor of performance, and task values are stronger predictors of choice and persistence (Wigfield & Eccles, 2000). However, the unique roles of different types of values for multiple key outcomes are not always examined in a single study, and when examined in a single study, the patterns appear to differ by age, group, and domain.

In Durik et al.'s (2006) work assessing both attainment/utility and interest values, 10th-grade students' attainment/utility values in English appeared to be most important for literacy-related career aspirations and choice of language arts courses, whereas interest value only predicted career aspirations. In another study focusing on 9th- and 10th-grade students, attainment/utility values in mathematics predicted choice of mathematics courses but not educational and occupational aspirations related to mathematics, and interest value did not predict any outcomes (Watt et al., 2012). Guo, Marsh, et al. (2015) showed that Grade 8 Hong Kong students' utility value in mathematics was more important for mathematics achievement than interest value, but their other study showed that 15-year-old Australian students' interest value in mathematics was more important for the statewide standardized test scores than utility value (Guo, Parker, et al., 2015), perhaps due to the different age groups, nationalities, or domains. Overall, attainment and utility values, compared to interest value, tended to predict career- and academic-related choice behavior, whereas interest value has shown relatively inconsistent patterns. In addition to domain and age-related differences, findings may have been mixed across studies due to various analytic approaches; thus, using a new analytic approach (i.e., latent interaction modeling) may provide a new perspective on these inconsistent findings from prior work.

The fourth type of value, perceived *costs*, describes students' reasons for *not* engaging in a task. Prior research supports the differentiation of three types of perceived costs, including *opportunity cost* (what one has to give up to complete a task), *effort cost* (the amount of anticipated effort required to succeed), and *psychological cost* (negative emotional states associated with fear of failure in the task; Perez et al., 2014). Situated expectancy–value theory suggests that perceived costs more strongly predict choice and persistence than does expectancy. Each cost is negatively associated with expectancy, values, and academic outcomes. However, there is little research examining the similar or differential roles of these different types of perceived costs for learning-related outcomes.

Although perceived costs are less often examined, consistent with the theoretical expectation, this construct has been found to negatively predict achievement, as well as academic choices and career intentions (Flake et al., 2015). Regarding the differential roles of different types of cost, Perez et al. (2014) found that undergraduate students' effort cost in science was the strongest predictor of intention to leave STEM majors, the opportunity cost was the next strongest predictor, and the psychological cost was not a significant predictor. By contrast, Flake et al. (2015) focused on college students with a variety of majors and found no differential patterns of the correlations with performance and long-term interest in a domain related to the class they were taking across these three cost types. Clarification of the unique patterns of perceived costs in engineering is needed to inform theoretical conceptualizations, as well as the design of practical interventions that have recently been introduced to reduce students' perceived costs (Cromley et al., 2020; Rosenzweig et al., 2020).

Relatively limited research has focused on expectancy, values, and costs in engineering. It is important to examine these constructs within the context of engineering, as one of the key assumptions of a situated expectancy–value theory is that expectancy and task values are formed based on a combination of students' past experiences, identities, and the sociocultural and historical meanings they attach to their participation in the domain (Eccles & Wigfield, 2020). Only a few studies have confirmed the applicability of situated expectancy–value theory to the engineering field. For example, there is evidence that expectancy more strongly predicted achievement, whereas values more strongly predicted career plans or retention in engineering majors (Jones et al., 2010), consistent with research in other domains. Further, in one study, interest, attainment, and career utility values were identified among engineering graduate students, largely consistent with value types in situated expectancy–value theory (Mosyjowski et al., 2017). However, these prior studies did not directly examine engineering students' cost perceptions suggested by situated expectancy–value theory; the researchers instead categorized several types of costs, including financial, balance, intellectual, and environmental costs (Mosyjowski et al., 2017; Peters & Daly, 2013). With regard to the function of each type of task value in engineering, qualitative evidence suggests that utility value is a primary factor in students' decisions to complete graduate degrees in engineering (Peters & Daly, 2013) and that attainment value was the most important factor in students' decisions to complete an undergraduate engineering degree (Matusovich et al., 2010). Quantitative studies are needed to test the comparative strength of these proposed relations between specific task values and several key engineering outcomes on a larger scale.

2.2 | Interaction between expectancy and values/costs

Although there has been a great deal of evidence for the additive and independent effects of expectancy and values on achievement-related outcomes, the classic expectancy–value theory model (Atkinson, 1957) assumed that achievement-related behavior was a result of the multiplicative function between expectancy and values. In other words, by this model, the positive effect of expectancy on engineering persistence would be stronger when students simultaneously hold a greater value on engineering coursework. Thus, testing the synergistic effect of expectancy and values, as compared to testing the independent effect of each variable, is necessary to more accurately understand how these two forms of motivation contribute to student success. For testing this synergistic effect, an interaction term is needed in a statistical model (e.g., multiple regression model). Typically, when using the multiple regression model, observed indicators that contain measurement error are multiplied to create a product term, thereby multiplying the measurement error. This enlarged error usually limits the ability to detect a significant interaction effect, and researchers considered this underestimation of the interaction effect size as one of the reasons for failing to observe the significant interaction of expectancy and values (Nagengast et al., 2011). Therefore, researchers have begun to employ latent interaction modeling, in which latent variables that are corrected for measurement error are used to generate product terms (Marsh et al., 2004) as an alternative to generating unbiased estimates of interaction effects proposed in the classic expectancy–value theory.

Prior studies on the latent interaction of expectancy and values have exclusively focused on secondary school students' motivation in specific domains, including science, mathematics, and English. Initially, these studies addressed only one or two types of value. For instance, across 57 countries, Nagengast et al. (2011) found that 15-year-old students' engagement in science activities and science-related career intentions were high when science expectancy and interest value were both high. In two subsequent studies, Guo, Marsh, et al. (2015); Guo, Parker, et al. (2015) included both interest and utility values in mathematics in the same model. In each study, a different value showed a significant interaction effect on mathematics achievement. These differences may be due to the different samples (8th graders in Hong Kong vs. 15-year-olds in Australia) or the statistically sensitive nature of including two highly correlated constructs in the same model. In a later study focusing on German high school students, multiple types of values and costs in mathematics were included in the same model (Guo et al., 2016); the researchers found a significant interaction between the global task value and expectancy, but interactions with each type of value were not significant, perhaps due to the different statistical approach (i.e., bi-factor models).

Other researchers have tested the expectancy × value interaction in separate models for each type of value and cost in a single study. For instance, Trautwein et al. (2012) found significant interaction effects on German secondary school students' mathematics and English achievement for all types of values and overall cost; this pattern of the findings was replicated in the Meyer et al. (2019) study, which also focused on German secondary school students. Taken together, when multiple types of values were included in the same model, the patterns of expectancy × value interaction were inconsistent (Guo et al., 2016; Guo, Marsh, et al., 2015; Guo, Parker, et al., 2015), and one of the possible reasons is high correlations among value types. In contrast, there were quite consistent patterns of the significant expectancy × value interaction when each type of value was included in separate models (Meyer et al., 2019; Nagengast et al., 2011; Trautwein et al., 2012). These empirical results of expectancy × value interaction studies highlight the usefulness of setting separate models for each type of value/cost in order to compare different types of value/cost in a single study to facilitate comparison.

Nonetheless, no prior research on the expectancy × value interaction has focused on engineering and how different types of costs (i.e., effort, psychological, and opportunity costs) interact with expectancy. However, the development and function of individuals' expectancy and values are influenced by the situation and sociocultural background where they are involved (Eccles & Wigfield, 2020), and the role of perceived costs may be particularly important in engineering (Mosyjowski et al., 2017; Peters & Daly, 2013). Furthermore, the prior work on the latent interaction between expectancy and values has focused on secondary school students. The interaction pattern could be distinct for students further along their educational paths as values may be increasingly important in college students' career-related choices and persistence (Eccles, 2009). Therefore, the current study seeks to address this gap by examining how each type of cost, as well as each type of value, interacts with expectancy in predicting undergraduates' engineering outcomes.

3 | THE CURRENT STUDY

3.1 | The purpose of the study

We examined how first-year undergraduate students' expectancy for success interacted with task values or perceived costs to predict engineering outcomes at the end of their first year. Of note, we assessed engineering academic self-efficacy, specifically students' evaluative perceptions of their capabilities in engineering-related courses (Mamaril et al., 2016), as a proxy for expectancy beliefs. Considering the conceptual similarities (Wigfield & Eccles, 2000) and consistent evidence that students empirically do not differentiate constructs related to competence beliefs, many researchers have used various competence perceptions as a proxy for expectancy. For instance, in prior research, Guo, Marsh, et al. (2015); Guo, Parker, et al. (2015); Guo et al. (2016) used self-concept (i.e., perceptions of ability) as a proxy for expectancy. In this study, we used self-efficacy as a proxy for expectancy based on the conceptual similarities between self-efficacy and expectancy (Eccles & Wigfield, 2020). Specifically, both expectancy (e.g., "How well do you expect to do in mathematics?") and self-efficacy (e.g., "I will be able to master the content in even the most challenging mathematics course if I try") are future-oriented perceptions in comparison to self-concept (e.g., "How good in mathematics are you?"), which reflects judgments based on past performance. The use of the future-oriented self-efficacy rather than self-concept as a proxy for expectancies is especially appropriate for this study, as participants were just beginning their engineering studies in college and thus were less likely to have prior performance experience on which to make self-concept judgments.

Four key outcomes were included to provide a more complete picture in explaining engineering students' choice, persistence, and achievement: engineering career intentions, aspirations for engineering graduate school, retention in an engineering major, and grades in foundational courses for engineering. Students' actual major at the end of the first year would be a strong indicator of persistence. However, since it is an early indicator of persistence and is thus subject to change, it is necessary to include other indicators of persistence. Grade point average (GPA) may be the most critical predictor of students' ultimate persistence in engineering. At the university where this study was conducted, a student's GPA upon completing prerequisite course requirements is the primary consideration for admission into the College of Engineering. Admission to the College of Engineering is required for students to access junior and senior-level courses. However, students who have the required GPA may still leave engineering, and major attrition may only be reflected later on in university records, so self-reported intentions and aspirations of persistence provide a more proximal indicator to shed light on students' plans.

We focused on first-year undergraduate students because the first year is a critical period when students assess their fit with their academic community and their major, with key implications for their educational and career pathways (Kuh et al., 2008). In addition, dropout or transfer to other majors occurs the most within the first year of college (Adamuti-Trache & Andres, 2008); thus, understanding how first-year engineering students' entering motivation functions to predict their success during their first exposure to engineering content is vitally important. Prior research has also highlighted the importance of first-year engineering students' expectancies and values/costs in predicting long-term outcomes such as academic achievement and career intentions in engineering (Jones et al., 2010).

Prior research suggested that three types of values (interest, attainment, and utility values) and costs (opportunity, effort, and psychological costs) distinctively predict outcomes both independently and by interacting with expectancy, supporting the necessity of examining the interaction for separate values and costs in the present study. Investigating separate models allows us to detect specific effects for each variable, as each has unique developmental origins and outcomes (Wigfield et al., 2016; Wigfield & Eccles, 1992), and to consider whether there were similar or unique patterns of main and interaction effects between engineering academic self-efficacy (closely related to expectancy) and each type of value and cost across the models. A similar approach can be found in prior work (e.g., Durik et al., 2006; Perez et al., 2014). Therefore, we created six different models, one for each type of value and cost, to examine the main effects of engineering academic self-efficacy (expectancy) and one type of value/cost, as well as the expectancy $\times$ value interaction effects on the outcomes (Figure 1) using latent interaction modeling. We developed the hypotheses based on situated expectancy–value theory's propositions but also considered the relevant empirical findings to predict the unique roles of different types of values and costs. Our specific research questions and hypotheses are as follows:

Research question: What are the main effects of engineering academic self-efficacy and each type of task value and perceived cost in predicting the four outcomes?

Hypothesis 1. *Engineering academic self-efficacy will more strongly predict grades (GPA), whereas values and costs will more strongly predict career intentions, aspirations, and engineering retention.*

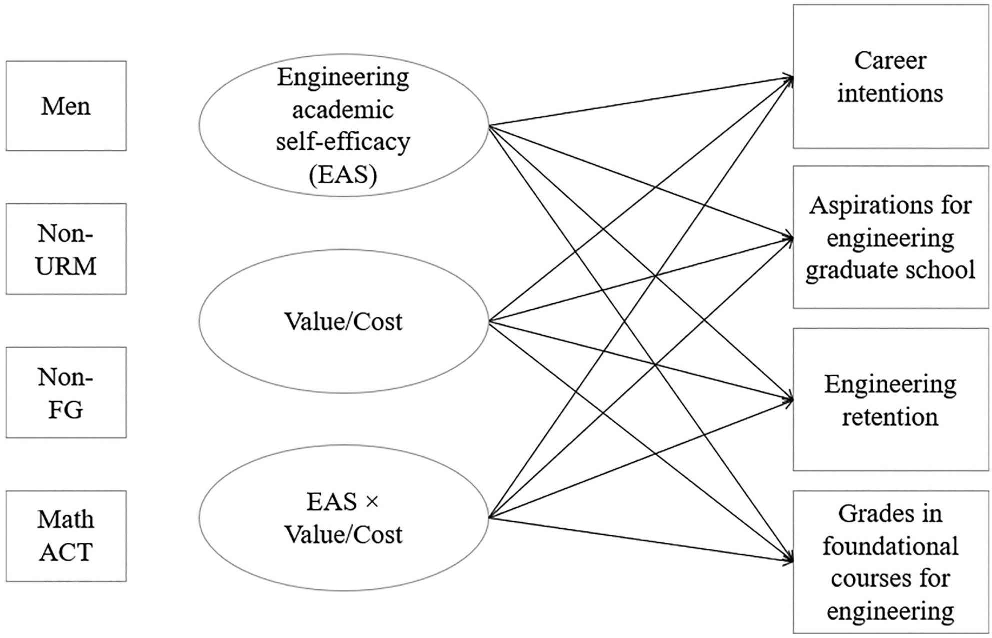

FIGURE 1 Structural equation model depicting the hypothesized relations among the key variables. The proposed model with a latent interaction variable, modeled separately for interest value (Model 1), attainment value (Model 2), utility value (Model 3), opportunity cost (Model 4), effort cost (Model 5), and psychological cost (Model 6). The paths of Men (women = 0; men = 1), Non-URM (non-underrepresented racial minority; URM = 0; non-URM = 1), Non-FG (nonfirst-generation; FG = 0; non-FG = 1), and Math ACT scores predicted both motivational (i.e., engineering academic self-efficacy, value/cost, and EAS × value/cost) and outcome (career intentions, aspirations for engineering graduate school, engineering retention, grades in foundational courses for engineering) variables. The motivational variables were measured at Time 1, and the outcome variables were measured at Time 2, except for grades in foundational courses for engineering (details are presented in Measures)

> **Hypothesis 2.** *Among the values, we hypothesize that attainment and utility values will be more strongly related to career intentions, aspirations, and engineering retention than will interest values.*

> **Hypothesis 3.** *Among the perceived costs, we hypothesize that effort costs will be more strongly associated with career intentions, aspirations, and engineering retention than opportunity and psychological costs.*

Research question: What are the interaction effects of engineering academic self-efficacy and each type of task value and perceived cost in predicting the four outcomes?

> **Hypothesis 4.** *Engineering academic self-efficacy will positively interact with values to predict career intentions, aspirations, engineering retention, and GPA; students with high values will have higher levels of outcomes when they also have high engineering academic self-efficacy.*

> **Hypothesis 5.** *Engineering academic self-efficacy will negatively interact with costs to predict career intentions, aspirations, engineering retention, and GPA; students with low costs will have higher levels of outcomes when they also have high engineering academic self-efficacy.*

3.2 | Researchers' positionality

The first author's research interest in students' motivation emerges from her own experiences in South Korea. The first author grew up in South Korea and completed her formal education in the country except for her doctoral training, which was completed in the United States. In South Korea, there is a great emphasis on education as a means to social and economic status, and students often report feeling a great deal of pressure to perform well in school. Her experiences as a Korean student in the past have led her to study how to support students' adaptive motivation and persistence in academic work. She is interested in issues of high attrition in STEM fields, as one of the potential reasons for high attrition is lack of motivation among students.

The authors of this work are within and outside of engineering education. The sixth and seventh authors have worked in the Department of Chemical Engineering and Materials Science as professors, and they have long made an effort to reduce dropout rates in the department. Their strong motivation to address the dropout issue aligns with the research interests of the rest of the authors within the discipline of educational psychology, which led us to collaborate to investigate engineering students' motivation in the current study. Our goal was to better understand engineering students' motivation through a lens of educational psychology, ultimately drawing implications for engineering education.

We are aware of potential biases as researchers who have collected a sample from the university where some of us have worked as a student, a researcher, or a professor. However, we believe our understanding of the university context helps us to more thoroughly and accurately uncover insights from our findings.

4 | METHOD

4.1 | Participants and procedure

Participants were engineering students at a large, public university in the United States. Students were eligible to participate in the study if they were first-year students enrolled as engineering majors. We recruited two cohorts of participants via email and at a freshman orientation program in the College of Engineering in Fall 2015 (Cohort 1) and Fall 2016 (Cohort 2). Across two cohorts, 2788 students were recruited, and 2420 students provided consent and enrolled in this study. At Time 1 (T1) in August just before students' first semester of college, of 2420 students, 1565 students (response rate: 60.9%) completed the T1 survey. At Time 2 (T2) 8 months after T1 and at the end of students' first year, 2420 students who enrolled in this study were all invited again via email and through their engineering courses regardless of whether they responded to the T1 survey, and 1803 students (response rate: 70.5%) completed the T2 survey. The T2 response rate, based on those who completed the T1 survey, was 67.3% ($n = 1054$). In total, the final data included 2420 participants who enrolled in this study from Cohorts 1 ($n = 1229$) and 2 ($n = 1191$), and their institutional data were collected.

The information on the sample characteristics by cohort is provided in Table 1. For the race/ethnicity responses, we grouped non-White or non-Asian students as underrepresented racial/ethnic minority (URM) students. Recently, to indicate racial/ethnic groups, it is encouraged to use the specific name of specific racial/ethnic groups rather than aggregating these groups. While acknowledging the importance of describing particular racial/ethnic groups, we chose to use the term URM to indicate non-White and non-Asian participants in this study for the following reasons. First, our purpose of including the variable of URM as a covariate was to account for the general sociocultural background characteristics known to be traditionally influenced motivational processes in STEM attrition, rather than identifying racial/ethnic group differences in motivation and outcomes per se. Second, the proportions of non-White and non-Asian groups in the dataset were small for analysis (<15.5%), and aggregating these groups as a URM maximizes the statistical power for our analysis.

According to aggregate statistics obtained from the College of Engineering, gender, URM status, first-generation (FG) college students status, and average math ACT score distributions for the study sample were comparable to those in the overall population of first-year engineering students during Fall 2015 and Fall 2016. Specifically, the population of first-year engineering majors was 21.9% women (compared with 24.7% women in the present study), 19.8% FG students (18.6% in the present study), and 12.4% URM students (11.7% in the present study). The overall engineering population had an average math ACT score of 27.21 (28.28 in the present study). The study, which was reviewed by the university's Institutional Review Board, was deemed exempt (IRB No. X12-375e).

4.2 | Measures

Data included survey responses and institutional records. The motivation items (engineering academic self-efficacy, values, and costs) were assessed at T1 before students encountered any coursework or programming provided by the College of Engineering. Students' motivational beliefs were measured before they had taken engineering courses in college, but their beliefs about self-efficacy, values, or costs in pursuing engineering could have been learned indirectly from others (e.g., teachers, parents, or counselors). Importantly, aside from how accurate or inaccurate they are, initial

TABLE 1 Demographic characteristics by cohort

	Cohort 1	Cohort 2
Gender		
Men	915 (74.5%)	907 (76.2%)
Women	314 (25.5%)	284 (23.8%)
Race		
African American or Black	88 (7.2%)	59 (5.0%)
Asian	251 (20.4%)	265 (22.3%)
White	788 (64.1%)	755 (63.4%)
Hispanic or Latino/a	60 (4.9%)	31 (2.6%)
Multiracial or other	27 (2.0%)	65 (5.5%)
Multiracial—URM	8 (0.7%)	32 (2.7%)
Multiracial—non-URM	12 (1.0%)	22 (1.8%)
URM		
URM	160 (13.0%)	124 (1.04%)
Non-URM	1051 (85.5%)	1042 (87.5%)
First-generation status		
First-generation	229 (18.6%)	221 (18.6%)
Nonfirst-generation	1000 (81.4%)	970 (81.4%)
Math ACT	28.16	28.41

Abbreviation: URM, underrepresented racial/ethnic minority (i.e., non-White and non-Asian participants).

motivation beliefs are crucial in shaping students' perceptions of such experiences during college. Also, although motivation beliefs change over time, these are assumed to be only somewhat malleable over time in response to normal experiences (Robinson et al., 2018). Focusing on students' entering motivation in engineering can provide a baseline understanding of which type of motivation belief might be most essential for intervention in their first year of college. Aspirations for engineering graduate school and engineering career intentions were assessed at T2. Retention in an engineering major and grades in foundational courses for engineering were collected directly from the institutional records at the end of the first year of college.

4.2.1 | Engineering academic self-efficacy, values, and costs

Engineering academic self-efficacy, values, and costs were all assessed on a five-point Likert scale (all items are presented in the Appendix), with 1 = "*strongly disagree*" and 5 = "*strongly agree*." For engineering academic self-efficacy, five items were used based on Mamaril et al.'s (2016) general engineering self-efficacy scale ($\alpha = .83$). To assess three types of task values in engineering, we used Conley's (2012) scales, modified to replace mathematics with engineering: interest (5 items; $\alpha = .87$), attainment (4 items; $\alpha = .75$), and utility (3 items; $\alpha = .76$) values.

We adapted items from Perez et al.'s (2014) scales to assess perceived costs in engineering. In Perez et al.'s (2014) factor analyses, students appeared to distinguish the three types of costs (opportunity, effort, and psychological costs) from one another, and each cost subscale was negatively associated with expectancy and values, as well as with college students' final grade, providing validity evidence for the measure. This measure was also originally validated with undergraduate students from a chemistry course for STEM majors. This can strengthen the validity of the cost subscales used in an engineering education setting in the current study due to the similar ages of the participants and the shared characteristics of chemistry and engineering as STEM domains. The reliabilities based on our data were adequate, including opportunity (3 items; $\alpha = .80$), effort (4 items; $\alpha = .76$), and psychological (5 items; $\alpha = .82$) costs. The scale for the opportunity cost originally comprised four items, but one item ("I would rather leave more time for fun than for something as intense as engineering") was excluded from analyses due to its relatively low factor loading ($\lambda = 0.46$; all factor loadings in the Appendix).

We conducted a confirmatory factor analysis (CFA) with seven latent variables, including engineering academic self-efficacy and all types of task values and perceived costs, suggesting their conceptual and empirical distinctions: $\chi^2(356) = 1328.23$, $p < .001$, Comparative Fit Index (CFI) $= 0.933$, Tucker-Lewis-Index $= 0.924$, Standardized Root Mean Square Residual $= 0.045$, Root Mean Square Error of Approximation (RMSEA) $= 0.042$ [90% Confidential Interval $= 0.039, 0.044$]. Of note, the chi-square (χ^2) test was not used in this case due to the large sample size. A larger sample size is more likely to obtain a significant chi-square (Hu & Bentler, 1999).

4.2.2 | Outcomes

As outcomes related to persistence in engineering, students' engineering career intentions, aspirations for engineering graduate school, retention in an engineering major, and grades in foundational courses for engineering (GPA) were included. We measured the distal outcomes 8 months after the first semester of college started, which was close to the end of the first year but prior to the final week. We administered the T2 surveys before end-of-the-semester events (e.g., final exams, project assignments) to help the reduce potential influences of these events on the quantity and quality of survey responses. Furthermore, measuring multiple outcomes 8 months later and controlling for prior achievement (mathematics ACT scores) and demographic factors (gender, URM status, and FG college student status) allows us to make stronger claims regarding the directionality of relations between motivation and outcomes. Examining distal outcomes is an important extension of prior latent interaction research that focused on concurrent outcomes.

Career intentions

A single item was used to measure career intentions in engineering (Estrada et al., 2011): "To what extent do you intend to pursue a career in engineering?" (1 = *definitely will not*, 10 = *definitely will*). For relatively clear and straightforward constructs such as career intentions, a simple item is less likely to introduce unnecessary error compared to a multi-item measure. Prior research has indicated that a single-item measure may be most appropriate for the clear and single-faceted nature of this construct (Gogol et al., 2014). Indeed, researchers have often measured career intentions with a single item and shown adequate validity based on the expected correlations with motivation and science career pursuit (Estrada et al., 2011; Woodcock et al., 2012).

Aspirations for engineering graduate school

A single item was used to measure aspirations for engineering graduate school to pursue graduate-level training in engineering (Jodl et al., 2001): "How far would you like to go in school? Mark all that apply." As we aimed to assess the specific education level that students wish to gain, the question is quite straightforward and does not require multiple items. Indeed, this single-item scale introduced by Eccles (1983) has often been used, and prior research has shown strong predictive validity through its relations with different student outcomes (Hill et al., 2004; Jodl et al., 2001). The responses were collapsed into a dichotomous variable to focus on aspirations for going to graduate school in an engineering-related field (coded as 1) versus aspirations for graduating college and/or pursuing a graduate degree in a nonengineering field (coded as 0).

Engineering retention

Students' majors were collected from institutional data at the end of the spring semester of their first year. Students were coded as having persisted in engineering if their major at the end of their second semester was within the College of Engineering (1 = *stayed in engineering*; 0 = *left engineering*).

Grades in foundational courses for engineering

The students' cumulative GPA obtained from engineering and engineering-related courses for the first year was obtained from institutional records. Grades included those from required courses for any engineering major at the university, including courses offered by the College of Engineering, elective courses related to engineering as listed on engineering major elective course lists (e.g., Composite Materials Processing, Chemical Reaction Engineering), and required prerequisite courses in domains such as mathematics, chemistry, and biology. At this university, all grades used a numerical system (4.0, 3.5, 3.0, 2.5, 2.0, 1.5, 1.0, 0.5, 0.0).

4.2.3 | Covariates

The students' gender (women = 0; men = 1), URM (i.e., non-White or non-Asian) group membership (URM = 0; Non-URM = 1), and FG college student status (FG = 0; Non-FG = 1) were collected from institutional records. ACT mathematics scores from the institutional records were used as a measure of academic achievement before entering college. For enrolling in introductory engineering courses, students were required to achieve a certain level of mathematics performance, and the ACT mathematics scores have provided strong evidence of predictive validity for college outcomes (Bettinger et al., 2013). Thus, we expected them to be especially informative for engineering students. The internal consistency reliabilities for ACT mathematics scores, reported on the ACT technical manual (ACT, 2017), also showed high-reliability values (0.90–0.92).

4.3 | Statistical analyses

Within the structural equation modeling framework in Mplus (Version 8), we examined the latent interaction between engineering academic self-efficacy and interest value (Model 1), attainment value (Model 2), utility value (Model 3), opportunity cost (Model 4), effort cost (Model 5), and psychological cost (Model 6) in predicting different outcomes, testing six models in total. To handle potential Type I error that might arise due to multiple hypothesis tests performed in each model, we computed adjusted *p*-values using the false discovery rate method (Benjamini & Hochberg, 1995). We used a robust maximum likelihood estimator (MLR) because it provides standard errors computed with Huber–White estimator, which corrects for the potential non-normality of the product indicators (Nagengast et al., 2011). Before the analysis, we standardized all indicators (continuous variables) and then created product indicators for the latent interactions based on the CFAs, using the unconstrained approach and matched pair-strategy (Marsh et al., 2004; details are presented in the Supporting Information).

In each of the six models (Models 1–6), we entered the main effects of engineering academic self-efficacy and one type of value or cost and the self-efficacy × value/cost interaction effect on all four outcomes (Figure 1). We obtained the collinearity statistics from the regression models estimating each of the four outcomes predicted by (1) engineering academic self-efficacy, three values, and three interaction terms (self-efficacy × each value) simultaneously, and (2) engineering academic self-efficacy, three costs, and three interaction terms (self-efficacy × each cost) simultaneously. As reported in Table S1, the results indicated that there exists high collinearity in all models. To reduce the concerns about collinearity and suppression effects due to the high correlations among the types of values and costs, we opted to test specific effects for each variable and consider whether there were similar or unique patterns of main and interaction effects between engineering academic self-efficacy and each type of value and cost across the models.

5 | RESULTS

Overall, missing data rates for specific items or indicators ranged from 0% to 40.3%, with an average missing rate of 33.8%, and specific variables ranged from 0% to 39.2%, with an average rate of 22.4% (Table S2). The missing rate of the institutional data was negligible (1–1.5%), whereas there was a fairly substantial amount of missingness in the survey data. Our missing analyses indicated that the current data might be more representative of students who achieved higher ACT math scores or were women or continuing generation (details are presented in the Supporting Information). Nonetheless, applying full information maximum likelihood to the current data under Missing At Random can yield less biased estimates (Enders, 2010). Further, we accounted for the patterns of missingness in main analyses by including all relevant variables, including gender, FG status, and ACT math scores within the models, reducing the concern about the potential influence of missing patterns on the final results. Next, we tested measurement invariance to ensure that each construct was interpreted in the same way across two cohorts (Table S3). The means, standard deviations, and correlations for the study variables for both cohorts are displayed in Table 2. The general patterns of correlations were consistent with our expectations and prior research.

Traditional model fit indices (e.g., χ^2, CFI, RMSEA) are not available when using the MLR estimator and a combination of continuous and categorical variables. Thus, we tested the appropriate measurement models prior to the main analyses. After confirming the measurement models (Table S4), we tested six different models examining the main effects of engineering academic self-efficacy and each type of value (or cost) and the self-efficacy × value/cost

TABLE 2 Means, standard deviations, and correlations of observed variables

	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Men	0.75	0.43	–													
2. Non-URM	0.88	0.32	0.05*	–												
3. Non-FG	0.81	0.39	−0.01	0.18***	–											
4. Math ACT	28.28	4.01	0.09***	0.39***	0.28***	–										
5. Self-efficacy	4.05	0.54	0.05*	−0.09**	−0.04	−0.01	–									
6. Interest	4.24	0.54	0.08**	−0.09***	−0.05*	0.01	0.57***	–								
7. Attainment	4.07	0.53	0.07*	−0.07**	−0.003	0.02	0.52***	0.63***	–							
8. Utility	4.56	0.48	0.01	−0.07**	0.01	−0.001	0.41***	0.53***	0.55***	–						
9. Opportunity	2.92	0.87	−0.01	0.04	−0.01	−0.05	−0.18***	−0.12***	0.02	−0.01	–					
10. Effort	2.30	0.76	0.07**	0.06*	−0.02	−0.06	−0.33***	−0.30***	−0.16***	−0.25***	0.51***	–				
11. Psych.	3.10	0.81	−0.18***	0.04	−0.01	−0.10***	−0.27***	−0.12***	0.03	0.02	0.55***	0.47***	–			
12. Car. intent.	8.21	2.08	−0.003	−0.06*	−0.01	0.02	0.24***	0.32***	0.22***	0.23***	−0.12***	−0.25***	−0.11***	–		
13. Edu. aspir.	0.47	0.50	0.03	−0.05*	−0.04	0.02	0.12***	0.15***	0.13***	0.10**	−0.04	−0.04	−0.05	0.26***	–	
14. Retention	0.93	0.25	0.01	−0.003	0.05*	0.09***	0.09**	0.10***	0.07**	0.08**	−0.02	−0.05	−0.02	0.47***	0.14***	–
15. EGR GPA	3.07	0.83	−0.08***	0.20***	0.15***	0.35***	0.06*	0.02	0.02	0.03	−0.01	−0.10***	−0.03	0.15***	0.05*	0.16***

Notes: Measures 6 to 8 are task values, and measures 9 to 11 are perceived costs. Men (0 = women; 1 = men); Non-URM (non-underrepresented racial minority; 0 = URM; 1 = non-URM); Non-FG (nonfirst-generation; 0 = FG; 1 = non-FG); Measures 5 to 11 were rated on a 5-point Likert scale; career intentions were rated on a 10-point Likert scale; aspirations for engineering graduate school (0 = college or graduate school in nonengineering; 1 = graduate school in engineering); retention in an engineering major (0 = left engineering; 1 = stayed in engineering).

Abbreviations: Car. intent., career intentions; Edu. aspir., aspirations for engineering graduate school; EGR GPA, grades in foundational courses for engineering; Psych, psychological cost; Retention, retention in an engineering major; Self-efficacy, engineering academic self-efficacy.

*$p < .05$; **$p < .01$; ***$p < .001$.

TABLE 3 Engineering academic self-efficacy and values predicting career intentions, educational aspirations, engineering retention, and engineering grade point average

	Career intentions				Educational aspirations				Engineering retention				Engineering GPA			
	b	SE	*β*	*p*	*b* [OR]	SE	*β*	*p*	*b* [OR]	SE	*β*	*p*	*b*	SE	*β*	*p*
Model 1: Interest																
Self-efficacy	0.14	0.12	.10	.376	0.09 [1.09]	0.21	0.04	.823	0.60 [1.82]	0.37	0.20	0.198	0.12	0.06	0.09	.086
Interest	**0.45**	**0.10**	**0.38**	**<.004**	**0.47 [1.60[a]]**	**0.17**	**0.21**	**.014**	**0.99 [2.69]**	**0.27**	**0.37**	**<0.004**	−0.07	0.05	−0.06	.362
EAS × Interest	**0.14**	**0.03**	**0.16**	**<.004**	−0.01 [0.99]	0.11	−0.01	.928	**0.61 [1.85]**	**0.21**	**0.30**	**0.012**	0.003	0.03	0.004	.928
Men	−0.12	0.06	−0.12	.086	0.04 [1.04]	0.12	0.02	.861	−0.18 [0.84]	0.22	−0.08	0.599	**−0.22**	**0.04**	**−0.22**	**<.004**
Non-URM	0.02	0.09	0.02	.880	−0.21 [0.81]	0.19	−0.11	.376	−0.25 [0.78]	0.34	−0.11	0.611	**0.38**	**0.08**	**0.39**	**<.004**
Non-FG	0.02	0.08	0.02	.872	−0.08 [0.92]	0.15	−0.04	.766	0.47 [1.59]	0.24	0.21	0.114	**0.17**	**0.06**	**0.17**	**.012**
Math ACT	0.04	0.03	0.04	.333	0.08 [1.08]	0.06	0.04	.362	**0.37 [1.45]**	**0.11**	**0.16**	**0.004**	**0.29**	**0.02**	**0.30**	**<.004**
R^2	0.21***				0.06**				0.35***				0.16***			
Model 2: Attain.																
Self-efficacy	0.26	0.20	0.20	.387	0.23 [1.25]	0.31	0.09	.597	0.71 [2.04]	0.55	0.26	0.387	0.09	0.06	0.07	.387
Attain.	0.37	0.26	0.24	.387	0.46 [1.58]	0.41	0.16	.406	0.84 [2.31]	0.71	0.26	0.387	−0.04	0.08	−0.02	.734
EAS × Attain.	0.08	0.05	0.09	.312	−0.12 [0.89]	0.14	−0.08	.519	0.31 [1.37]	0.14	0.18	0.131	−0.02	0.03	−0.02	.603
Men	−0.11	0.06	−0.11	.196	0.03 [1.04]	0.12	0.02	.840	−0.11 [0.89]	0.21	−0.05	0.691	**−0.22**	**0.04**	**−0.23**	**<.007**
Non-URM	−0.02	0.09	−0.02	.869	−0.23 [0.79]	0.19	−0.12	.387	−0.32 [0.73]	0.33	−0.15	0.491	**0.38**	**0.08**	**0.39**	**<.007**
Non-FG	−0.01	0.08	−0.01	.869	−0.13 [0.88]	0.16	−0.07	.560	0.38 [1.46]	0.24	0.18	0.361	**0.18**	**0.06**	**0.18**	**.017**
Math ACT	0.04	0.03	0.04	.387	0.08 [1.08]	0.06	0.04	.387	**0.36 [1.43]**	**0.11**	**0.17**	**0.007**	**0.29**	**0.02**	**0.30**	**<.007**
R^2	0.16***				0.07*				0.26***				0.16***			
Model 3: Utility																
Self-efficacy	0.18	0.11	0.14	.217	0.13 [1.14]	0.19	0.05	.605	0.47 [1.60]	0.33	0.17	0.276	0.06	0.05	0.04	.386
Utility	**0.64**	**0.16**	**0.40**	**<.005**	**0.73 [2.07[a]]**	**0.26**	**0.25**	**.014**	**1.52 [4.57]**	**0.45**	**0.44**	**0.005**	0.02	0.07	0.01	.837
EAS × Utility	**0.16**	**0.05**	**0.21**	**.012**	0.11 [1.12]	0.09	0.08	.386	**0.48 [1.62]**	**0.17**	**0.30**	**0.014**	−0.01	0.03	−0.01	.834
Men	−0.10	0.06	−0.10	.217	0.06 [1.06]	0.12	0.03	.736	−0.09 [0.92]	0.22	−0.04	0.781	**−0.22**	**0.04**	**−0.23**	**<.005**
Non-URM	−0.01	0.09	−0.01	.942	−0.22 [0.80]	0.19	−0.12	.386	−0.25 [0.78]	0.34	−0.11	0.605	**0.38**	**0.08**	**0.40**	**<.005**
Non-FG	−0.05	0.08	−0.05	.605	−0.16 [0.85]	0.16	−0.09	.434	0.29 [1.34]	0.26	0.13	0.386	**0.17**	**0.06**	**0.18**	**.014**
Math ACT	0.05	0.03	0.05	.226	0.09 [1.10]	0.06	0.05	.276	**0.39 [1.48]**	**0.11**	**0.18**	**<0.005**	**0.29**	**0.02**	**0.30**	**<.005**
R^2	0.21***				0.07**				0.31***				0.16***			

Notes: All *p* values are adjusted using the Benjamini–Hochberg procedure. In each model, the relations of Men, Non-URM, Non-FG, and math ACT scores to engineering academic self-efficacy and values were also controlled for (results are presented in Table S7). Men (0 = women; 1 = men); Non-URM (0 = URM; 1 = non-URM); Non-FG (0 = first generation; 1 = nonfirst-generation). Values in bold represent statistically significant findings ($p < .05$).

Abbreviations: Attain., attainment value; *b*, unstandardized coefficients; EAS × Value, interaction between engineering academic self-efficacy and each type of value; Educational aspirations, aspirations for engineering graduate school; Engineering GPA, grades in foundational courses for engineering; Interest, interest value; Non-FG, non-first-generation; Non-URM, non-underrepresented racial minority; OR, odds ratio; *p*, *p* values for unstandardized coefficients; R^2, coefficient of determination; SE, standard errors; Self-efficacy (EAS), engineering academic self-efficacy; Utility, utility value; *β*, standardized coefficients.

[a]The estimates OR are the odds ratios from logit regression. As an example of interpreting the odds ratios, for aspirations for engineering graduate school, students with higher interest value (one standard deviation above the mean) were 1.23 times (or 23%), and those with higher utility value were 1.28 times (or 28%) more likely to aspire to go to graduate school in engineering at the end of their first year, compared to students with a mean level of interest or utility value.

*$p < .05$; **$p < .01$; ***$p < .001$.

TABLE 4 Engineering academic self-efficacy and costs predicting career intentions, educational aspirations, engineering retention, and engineering grade point average

	Career intentions				Educational aspirations				Engineering retention				Engineering GPA			
	b	SE	*β*	*p*	*b* [OR]	SE	*β*	*p*	*b* [OR]	SE	*β*	*p*	*b*	SE	*β*	*p*
Model 4: Oppor.																
Self-efficacy	**0.43**	**0.07**	**0.33**	**<.004**	**0.46 [1.59]**	**0.12**	**0.19**	**<.004**	**0.94 [2.55]**	**0.22**	**0.35**	**<.004**	0.09	0.04	0.07	.090
Oppor.	−0.08	0.08	−0.07	.424	−0.13 [0.88]	0.12	−0.06	.424	0.06 [1.06]	0.29	0.03	.863	0.05	0.04	0.05	.358
EAS × Oppor.	0.15	0.12	0.11	.388	0.15 [1.16]	0.18	0.06	.527	0.39 [1.48]	0.34	0.15	.390	−0.04	0.04	−0.04	.444
Men	−0.09	0.06	−0.09	.262	0.06 [1.06]	0.12	0.03	.703	−0.08 [0.93]	0.21	−0.04	.776	**−0.22**	**0.04**	**−0.23**	**<.004**
Non-URM	−0.04	0.09	−0.04	.703	−0.24 [0.79]	0.19	−0.13	.388	−0.47 [0.62]	0.32	−0.23	.336	**0.38**	**0.08**	**0.39**	**<.004**
Non-FG	−0.001	0.08	−0.001	.994	−0.11 [0.90]	0.15	−0.06	.595	0.39 [1.48]	0.23	0.19	.255	**0.18**	**0.06**	**0.18**	**.011**
Math ACT	0.04	0.03	0.03	.390	0.07 [1.08]	0.06	0.04	.390	**0.37 [1.45]**	**0.11**	**0.18**	**<.004**	**0.29**	**0.02**	**0.30**	**<.004**
R^2	0.14**				0.05*				0.19**				0.16**			
Model 5: Effort																
Self-efficacy	0.20	0.11	0.15	.165	0.21 [1.23]	0.17	0.08	.431	0.51 [1.66]	0.33	0.18	.296	0.02	0.05	0.02	.790
Effort	**−0.51**	**0.13**	**−0.33**	**<.007**	**−0.56 [0.57]**	**0.21**	**−0.19**	**.028**	**−0.96 [0.38]**	**0.33**	**−0.30**	**.014**	−0.11	0.06	−0.08	.159
EAS × Effort	0.06	0.08	0.05	.550	0.13 [1.14]	0.16	0.06	.547	−0.03 [0.97]	0.20	−0.01	.888	−0.03	0.03	−0.03	.547
Men	−0.02	0.06	−0.02	.810	0.14 [1.15]	0.13	0.08	.453	0.07 [1.07]	0.22	0.03	.810	**−0.20**	**0.05**	**−0.21**	**<.007**
Non-URM	−0.05	0.09	−0.05	.721	−0.26 [0.77]	0.19	−0.14	.388	−0.43 [0.65]	0.34	−0.21	.404	**0.39**	**0.08**	**0.41**	**<.007**
Non-FG	−0.02	0.08	−0.02	.827	−0.13 [0.88]	0.16	−0.07	.547	0.38 [1.46]	0.24	0.18	.290	**0.17**	**0.06**	**0.18**	**.016**
Math ACT	0.03	0.03	0.03	.547	0.07 [1.07]	0.07	0.04	.471	**0.32 [1.37]**	**0.10**	**0.15**	**.011**	**0.29**	**0.02**	**0.29**	**<.007**
R^2	0.18**				0.07*				0.22**				0.16**			
Model 6: Psych.																
Self-efficacy	**0.46**	**0.09**	**0.35**	**<.004**	**0.53 [1.70]**	**0.13**	**0.22**	**<.004**	**1.04 [2.83]**	**0.25**	**0.39**	**<.004**	0.08	0.04	0.07	.134
Psych.	−0.03	0.12	−0.02	.868	0.02 [1.02]	0.18	0.01	.935	0.14 [1.15]	0.42	0.05	.868	0.03	0.05	0.02	.868
EAS × Psych.	0.03	0.12	0.02	.868	−0.06 [0.94]	0.19	−0.02	.868	0.09 [1.09]	0.32	0.03	.868	−0.04	0.05	−0.03	.616
Men	−0.11	0.07	−0.11	.239	0.06 [1.06]	0.13	0.03	.868	−0.06 [0.94]	0.23	−0.03	.868	**−0.21**	**0.05**	**−0.22**	**<.004**
Non-URM	−0.04	0.09	−0.04	.868	−0.24 [0.79]	0.19	−0.13	.444	−0.48 [0.62]	0.33	−0.24	.352	**0.38**	**0.08**	**0.40**	**<.004**
Non-FG	0.01	0.08	0.01	.935	−0.10 [0.91]	0.15	−0.05	.868	0.42 [1.52]	0.23	0.21	.185	**0.18**	**0.06**	**0.18**	**.011**
Math ACT	0.04	0.03	0.04	.497	0.08 [1.08]	0.07	0.04	.444	**0.37 [1.45]**	**0.12**	**0.18**	**.004**	**0.29**	**0.02**	**0.30**	**<.004**
R^2	0.13**				0.05*				0.19**				0.16**			

Notes: All p values are adjusted using the Benjamini–Hochberg procedure. In each model, the relations of Men, Non-URM, Non-FG, and math ACT scores to engineering academic self-efficacy and costs were also controlled for (results are presented in Table S7). The estimates OR are the odds ratios calculated from logit regression. Men (0 = women; 1 = men); Non-URM (0 = URM; 1 = non-URM); Non-FG (0 = first generation; 1 = nonfirst-generation). Values in bold represent statistically significant findings ($p < .05$).

Abbreviations: b, unstandardized coefficients; EAS × Cost, interaction between engineering academic self-efficacy and each type of cost; Educational aspirations, aspirations for engineering graduate school; Effort, effort cost; Engineering GPA, grades in foundational courses for engineering; Non-FG, nonfirst-generation; Non-URM, non-underrepresented racial minority; Oppor., opportunity cost; OR, odds ratio; p, p values for unstandardized coefficients; Psych., psychological cost; R^2, coefficient of determination; SE, standard errors; Self-efficacy (EAS), engineering academic self-efficacy; β, standardized coefficients.

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

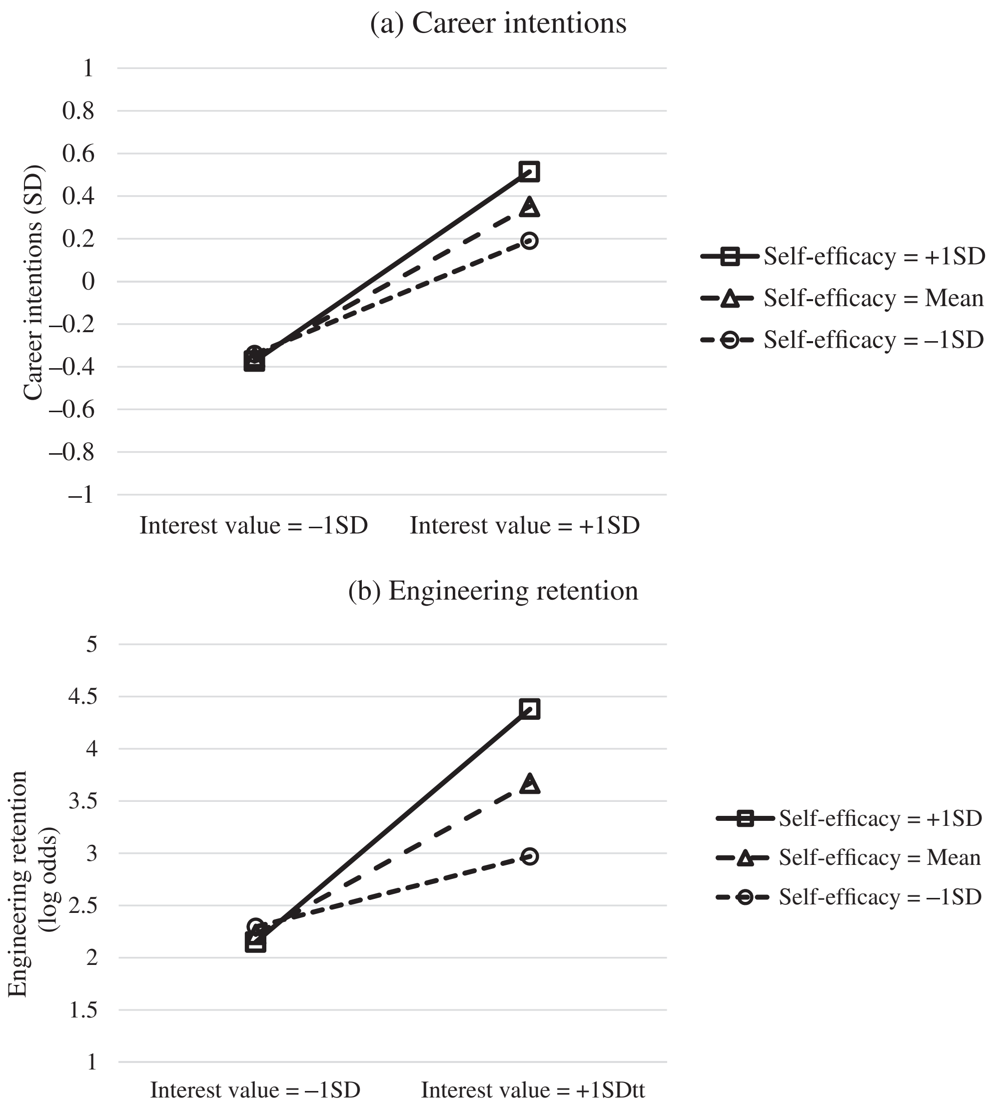

FIGURE 2 Expectancy × interest value interaction predicting career intentions and engineering retention. The model-implied regression lines are for women, URM (underrepresented racial minority), and FG (first-generation) students' latent interaction between engineering academic self-efficacy and interest value. SD, standard deviations

interaction effect on four outcomes, and the outcomes were all included in each model (Figure 1). The results for the models without the interaction terms are presented in Tables S5 and S6. Overall, the significant patterns of the main effects in the final models, including the interaction terms (Tables 3 and 4) remained largely the same as those from the models without the interaction terms. For the final models, including the interaction terms, the estimates of demographic variables predicting motivational factors are presented in Table S7, and the indirect effects of demographic predictors on engineering outcomes via motivational factors are presented in Table S8 (we did not report the estimates specifically here as the analysis is outside the scope of the research questions). Below, we report the findings from the final models, including the interaction terms.

In the interest-value model (Model 1), engineering academic self-efficacy did not significantly predict any outcomes. Interest value predicted all outcomes (β's $= 0.21$ to 0.38, p's $< .014$) except GPA. Interest value significantly interacted with self-efficacy to predict career intentions ($\beta = 0.16$, $p < .004$) and engineering retentions ($\beta = 0.30$, $p = .012$). The model-implied regression lines in Figure 2a,b illustrate that career intentions and engineering retentions were particularly high when both self-efficacy and interest value were relatively high. Thus, students who were efficacious at engineering-related tasks, *and* were simultaneously interested in the tasks, had stronger intentions to pursue a career in engineering and were more likely to stay in engineering at the end of their first year of college, compared to those who were efficacious at engineering-related tasks *or* interested in the tasks. The primary model, including the

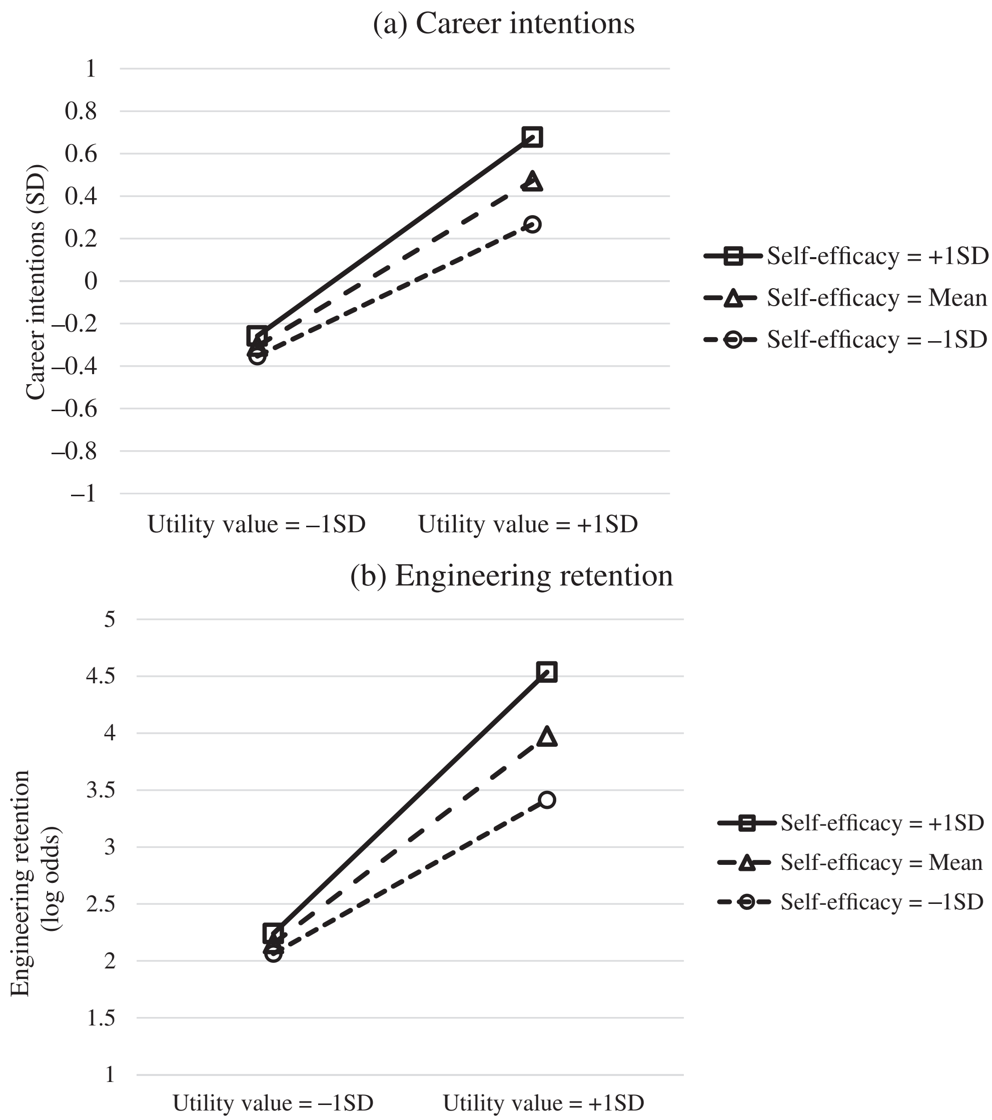

FIGURE 3 Expectancy × utility value interaction predicting career intentions and engineering retention. The model-implied regression lines are for women, URM (underrepresented racial minority), and FG (first-generation) students' latent interaction between engineering academic self-efficacy and utility value. SD, standard deviations

interaction term, explained more variance in career intentions ($R^2 = 0.21$) and engineering retention ($R^2 = 0.35$) relative to the model without the interaction term ($R^2 = 0.18$–0.22; Table S5), but there were no differences in variance explained for the other outcomes.

In the attainment-value model (Model 2), there were no significant main effects of self-efficacy or attainment value on the outcomes, as well as no significant interaction effect. Despite the nonsignificant interaction effect, the primary model, including the interaction term, explained more variance in engineering retention ($R^2 = 0.26$) relative to the model without the interaction term ($R^2 = 0.18$), but there were only minimal differences or no differences in variance explained for the other outcomes.

In the utility-value model (Model 3), similar to Model 1, utility value predicted all outcomes (β's $= 0.25$ to 0.44, p's $< .014$) except GPA. However, self-efficacy did not predict any outcomes. Utility value significantly interacted with self-efficacy to predict career intentions ($\beta = 0.21$, $p = .012$) and engineering retention ($\beta = 0.30$, $p = .014$), suggesting career intentions and engineering retention were even higher when both self-efficacy and utility value were high (Figure 3a,b). The primary model, including the interaction term, explained more variance in career intentions ($R^2 = 0.21$) and engineering retention ($R^2 = 0.31$) relative to the model without the interaction term ($R^2 = 0.15$–0.19), but there were only minimal differences or no differences in variance explained for the other outcomes.

The opportunity-cost (Model 4) and the psychological-cost (Model 6) models showed similar patterns of significant paths. Whereas self-efficacy predicted all outcomes (Model 4: β's = 0.19 to 0.35, p's < .004; Model 6: β's = 0.22 to 0.39, p's < .004) except GPA, opportunity cost or psychological cost did not predict any outcomes. No significant interaction effect was found. There were only minimal differences or no differences in variance explained for all outcomes between the primary model, including the interaction term ($R^2 = 0.05$–0.19) and the model without the interaction term ($R^2 = 0.05$–0.19; Table S6).

In the effort-cost model (Model 5), self-efficacy did not predict any outcomes, whereas effort costs predicted all outcomes (β's = −0.33 to −0.19, p's < .028) except GPA. There was no significant interaction effect. There were only minimal differences or no differences in variance explained for all outcomes between the primary model, including the interaction term ($R^2 = 0.07$–0.22) and the model without the interaction term ($R^2 = 0.06$–0.21).

Overall, engineering academic self-efficacy did not significantly predict GPA across all models. In the opportunity-cost and psychological-cost models, self-efficacy predicted other persistence outcomes. Interest value, utility value, and effort costs independently predicted engineering persistence. The interactions in the interest- and utility-value models suggest that feeling competent and placing a high value on engineering at the same time may be especially related to higher levels of career intentions and retention in engineering, as compared to either feeling competent or placing a high value on engineering alone. Importantly, having high self-efficacy does not relate to career intentions and retention in an engineering major if students do not view engineering as enjoyable or useful. Additionally, we found no evidence that perceived costs interacted with self-efficacy.

6 | DISCUSSION

This study investigated first-year undergraduate engineering students' self-efficacy, values, costs, and indicators of early engineering persistence in college. In particular, we assessed multiple dimensions of task values and perceived costs in a single study, which provides a nuanced understanding of potentially differential roles of value/cost beliefs in predicting engineering persistence. In addition, this study affirms the importance of supporting both engineering academic self-efficacy and values, as opposed to supporting only self-efficacy or values. As such, the current findings point to specific strategies that may be used in engineering education.

6.1 | Roles of different types of values and costs in situated expectancy–value theory

The findings associated with each hypothesis are summarized in Table 5. With respect to main effects, we first hypothesized that self-efficacy would predict grades in all models (Hypothesis 1). This hypothesis was not supported in that the main effects of self-efficacy on GPA were not significant in any of the models. These nonsignificant main effects, which mirror the weak bivariate correlation observed between engineering academic self-efficacy and GPA (r = .06) in the current data, might reflect the fact that in the first year of college, engineering students take a number of engineering-related prerequisite courses in other areas (e.g., mathematics, chemistry). At this institution, engineering students often take only two or fewer engineering courses during their first year, with one course having very little variability in grades (e.g., most students earn a 4.0 on a 4.0 scale). In other words, students may not view the courses that make up their GPA as engineering courses per se because they include both prerequisites and major, specific courses. The different levels of measurement for self-efficacy and GPA could be a reason for the nonsignificant effects of engineering academic self-efficacy in this study. However, we note that, in our case, it is also possible that engineering academic self-efficacy could still support students' achievement in the courses in other areas (e.g., mathematics, chemistry) because these courses are included as College Requirements or Major Requirements for engineering at the institution. For clarifying the association between engineering academic self-efficacy and GPA, future research needs to focus on the prediction of engineering-specific GPA. Alternately, considering the timing of our measurement, first-year students' self-efficacy beliefs may not accurately reflect their actual ability in engineering. Thus, it is worthwhile to measure engineering motivation later in college to see if stronger relations are identified as expected.

We also hypothesized that values would predict engineering career intentions, aspirations for engineering graduate school, and engineering retention (Hypothesis 1). This hypothesis was supported in the interest- and utility-value models only. Distinct from interest and utility values, attainment value is the most identity-related form of value (Eccles, 2009). As prior research suggests that college is a key time for students' developing career and academic

TABLE 5 Hypotheses and associated findings in the current study

Hypothesis	Findings
What are the main effects of engineering academic self-efficacy and each type of task value and perceived cost in predicting the four outcomes?	
H1. Engineering academic self-efficacy will more strongly predict grades (GPA), whereas values and costs will more strongly predict career intentions, aspirations, and engineering retention.	Engineering academic self-efficacy did not predict grades, but engineering academic self-efficacy significantly predicted all other outcomes in the opportunity- and psychological-cost models. Some values and costs significantly predicted engineering persistence outcomes except GPA.
H2. Among the values, we hypothesize that attainment and utility values will be more strongly related to career intentions, aspirations, and engineering retention than will interest values.	Only interest value and utility value significantly predicted career intentions, aspirations, and engineering retention.
H3. Among the perceived costs, we hypothesize that effort costs will be more strongly associated with career intentions, aspirations, and engineering retention than opportunity and psychological costs.	Only effort costs significantly predicted career intentions, aspirations, and engineering retention.
What are the interaction effects of engineering academic self-efficacy and each type of task value and perceived cost in predicting the four outcomes?	
H4. Engineering academic self-efficacy will positively interact with values to predict career intentions, aspirations, engineering retention, and GPA; students with high values will have higher levels of outcomes when they also have high engineering academic self-efficacy.	There were positive interactions with engineering academic self-efficacy in predicting career intentions and aspirations in the interest- and utility-value models only.
H5. Engineering academic self-efficacy will negatively interact with costs to predict career intentions, aspirations, engineering retention, and GPA; students with low costs will have higher levels of outcomes when they also have high engineering academic self-efficacy.	There were no significant interactions with engineering academic self-efficacy for costs.

identities (Roisman et al., 2004), attainment value might function differently from the other values for college students (Robinson et al., 2018). Such developmental characteristics, such as its relative stability and strong predictive power for later university outcomes, could lead to nonsignificant main and interaction effects of attainment value in early college, contrary to our expectations (Hypothesis 2 and 4).

Effort costs predicted all the outcomes except GPA; however, other costs did not, in alignment with prior research (Perez et al., 2014) and supporting our hypothesis that effort costs would be most likely to predict the outcomes compared to the other costs (Hypothesis 3). In our opportunity- and psychological-cost models, self-efficacy, not costs, significantly predicted some outcomes, whereas in the effort-cost model, effort costs, but not self-efficacy, predicted the outcomes. These results suggest that students who think engineering coursework is not worth the effort may be less likely to pursue engineering-related behaviors, regardless of their self-efficacy. However, opportunity cost or psychological cost appeared to be less predictive of the outcomes than self-efficacy. Perhaps if students feel competent about the engineering-related coursework, the cost of giving up other valued activities or worrying about performance on engineering might not be as concerning. These findings suggest that when intending to buffer students' perceived costs in engineering-related coursework, reducing effort costs needs to be prioritized compared to opportunity or psychological costs. For example, a professor might reduce students' effort costs by explaining why the effort is needed to be successful in engineering and how it can be worth it in the end.

Regarding the interaction effect hypotheses, we found some significant interaction effects suggesting that the relations between self-efficacy and persistence outcomes (particularly career intentions and engineering retention) depend on values and vice versa (Hypothesis 4). In the interest- and utility-value models, although there were significant main effects of values, students' career intentions and retention in an engineering major were even higher when self-efficacy was also high (Figures 2a,b, and 3a,b). Of note, in these two models, self-efficacy alone was not a significant predictor of career intentions or engineering retention. However, self-efficacy further facilitated the positive roles of interest- or utility-values. These interaction effects of values and self-efficacy suggest that it is important for engineering educators to focus on supporting engineering academic self-efficacy for students who are interested in engineering or who perceive its usefulness for their future in order to achieve synergistic effects on engineering persistence.

Although having high self-efficacy and value together showed a synergistic effect on outcomes, we did not observe that having high interest- or utility-value with low self-efficacy had a detrimental effect on outcomes. That is, high task values were not detrimental when self-efficacy was low and vice versa; as long as the value is high, career intentions and engineering retention are also high. Possibly, even in the interaction effects, the role of values in choice and persistence behaviors may be more crucial than that of self-efficacy. Our findings bolster the importance of supporting values in engineering education, especially as values (and self-efficacy) tend to decline during undergraduate studies.

The expected significant multiplicative function was found only for some values but not for costs, and this pattern was inconsistent with our hypothesis (Hypothesis 5) and prior work (Trautwein et al., 2012), showing interaction effects for all values and overall costs. It may be that prior studies examined how a composite factor of perceived costs predicted outcomes, but they did not examine the unique roles of each type of perceived cost. Another possibility is that there were differences in the nature of the sample in terms of students' ages. In the current study, participants had already made an initial decision about their major. Thus, even if working on engineering coursework is perceived as a high-cost pursuit, students have already demonstrated a willingness to pursue engineering, and the high-cost perceptions may not deter them during the first year. Students' earlier decisions about their major could lead to weaker-than-expected relations to the engineering outcomes at the end of the first year. It is also possible that patterns could vary for individuals, with perceived costs being detrimental for some students but not all. Specifically, engineering persistence may have unique implications at the intersection of students' gender, race/ethnicity, and FG college status, as situated expectancy–value theory stresses the impact of the cultural background on the development of individuals' expectancy and values (Eccles & Wigfield, 2020; Totonchi et al., 2021). Future research can investigate such intersectional effects on engineering persistence, which can add nuance to guidelines for how to help students who are generally underrepresented in an engineering field.

6.2 | Limitations and future directions

We note a few limitations in the current study to guide future research. First, we measured students' motivation at the beginning of their university studies before they had begun coursework, and other university experiences that can shape students' motivation over time. Assessing students' motivation in later months and years of college could provide unique insights into how students' motivation, shaped based on their own experience with engineering coursework, functions in engineering persistence in a more precise way. In other words, students' engineering-specific motivation may be more established after they experience engineering coursework. However, we maintain that students' confidence and reasons for engaging in engineering at the beginning of their studies, even before experiencing their courses, is an important indicator, as students' engagement with and perceptions of their subsequent experiences are very likely influenced by their incoming beliefs (Bandura, 1997). Since individuals' motivation can shift over time, accounting for the nature of malleability in engineering motivation in future research would also clarify the relation between motivation and later engineering-related outcomes. For instance, examining time-related changes in expectancy and values/costs could address how the development of motivation contributes to engineering persistence.

In addition, for the purpose of our analysis in this study, we chose to aggregate non-Asian and non-White individuals as a URM group while we acknowledge the importance of being specific and sensitive to the variability that exists between and within different racial and ethnic groups. Future research needs to investigate similarities and differences in the roles of expectancy and values/costs in engineering persistence outcomes across different racial and ethnic groups. Specifically, it would be useful to examine whether the main and interaction effects of expectancy and values/costs may be similar or different across diverse populations by using a multigroup approach.

6.3 | Practical implications

The current findings provide implications for motivation interventions in engineering or STEM fields more broadly. Our results highlight the importance of simultaneously supporting multiple forms of engineering motivation, including both values and academic self-efficacy. Doing so can yield the highest levels of persistence outcomes for students, as our findings suggest that students who both value engineering *and* feel confident in their ability to do engineering coursework were most likely to remain in engineering at the end of the first year and endorsed stronger career intentions to pursue engineering. The need to support multiple forms of motivation highlights the potential benefits of integrative motivational interventions designed to support multiple motivational constructs simultaneously. For instance, Linnenbrink-Garcia et al. (2018) developed a 2-week summer science program for undergraduates that drew from five motivational design principles (use real-world challenging tasks, provide choice, support active involvement, support belonging, use effort-based evaluation) to successfully support early undergraduates' self-efficacy and values in science. This multifaceted intervention also showed promising results for supporting undergraduates' persistence in science.

Such an approach could readily be applied to engineering classrooms as well. For instance, as a way of supporting self-efficacy, students who are unsure about their own capabilities to successfully complete engineering tasks can benefit from vicarious experiences such as exposure to role models who had common difficulties (e.g., struggled in introductory required courses) but overcame barriers to becoming engineers. Even for students who are quite competent about engineering tasks, our findings of synergistic effects of self-efficacy and values suggest the importance of promoting task values while holding their self-efficacy high in order to maximize the positive effects of motivational beliefs on engineering persistence. For example, as shown in some current intervention approaches, making engineering courses personally relevant can help students find the usefulness of engineering work in their career path (Hulleman et al., 2010; Hulleman & Harackiewicz, 2009). As such, class activities for supporting self-efficacy should be provided along with activities that illustrate the relevance of the material to students' lives, perhaps, including value interventions, bringing synergistic effects of expectancy and values beyond the independent effect of each construct. Even for courses in which the vast majority of students receive high grades, their longer-term persistence may be harmed if they do not have experiences that support their interest in engineering or their recognition of its usefulness and importance to their identities.

6.4 | Conclusion

For informing strategies for promoting students' engineering persistence, this study's findings suggest the importance of supporting both engineering academic self-efficacy and task values simultaneously in engineering coursework, as opposed to supporting only one of these motivational constructs. This means that supporting only engineering students' confidence or providing a rationale for why a task is valuable may not be sufficient. Of note, we found evidence of this multiplicative function of engineering academic self-efficacy and interest/utility value only, but not for self-efficacy and utility value or perceived costs in engineering. Thus, an effective way of supporting college students' engineering persistence may differ depending on which motivational construct (e.g., values or costs) is targeted. The current findings contribute important knowledge to situated expectancy–value theory about how expectancy and value beliefs function together. We believe these theoretical findings can also inform educational policies and practices by providing insights for how to intervene in support of students' motivation and success.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

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APPENDIX

SURVEY ITEMS FOR MOTIVATIONAL BELIEFS IN ENGINEERING

Values in parentheses are estimated standardized factor loadings for each item in the CFA model with seven latent variables, including engineering academic self-efficacy and all types of task values and perceived costs.

Engineering academic self-efficacy (adapted from Mamaril et al., 2016)

1. I'm certain I can master the content in the engineering-related courses I am taking this semester. (0.73)
2. I will be able to master the content in even the most challenging engineering course if I try. (0.67)
3. I will be able to do a good job on almost all my engineering coursework if I do not give up. (0.64)
4. I'm confident that I can learn the content taught in my engineering-related courses. (0.74)
5. I'm certain I can earn a good grade in my engineering-related courses. (0.76)

Task values (adapted from Conley, 2012)

Interest value:
1. I enjoy the subject of engineering. (0.82)
2. I enjoy doing engineering. (0.79)
3. Engineering is exciting to me. (0.64)
4. I am fascinated by engineering. (0.70)
5. I like engineering. (0.81)

Attainment value:
1. It is important for me to be a person who reasons like an engineer. (0.65)
2. It is important for me to be someone who is good at solving problems that involve engineering. (0.70)
3. Being someone who is good at engineering is important to me. (0.69)
4. Being good in engineering is an important part of who I am. (0.59)

Utility value:
1. Engineering is valuable because it will help me in the future. (0.69)
2. Engineering will be useful for me later in life. (0.76)
3. Being good in engineering will be important for my future (like when I get a job or go to graduate school). (0.68)

Perceived costs (adapted from Perez et al., 2014)

Opportunity cost:
1. I'm concerned that I have to give up a lot to do well in engineering. (0.85)
2. I'm concerned that success in engineering requires that I give up other activities I enjoy. (0.80)
3. I'm concerned about losing track of valuable relationships because of the work required for engineering. (0.63)
4. I would rather leave more time for fun than for something as intense as engineering (dropped). (0.46).

Effort cost:
1. When I think about the hard work needed to be successful in engineering, I am not sure that studying engineering is going to be worth it in the end. (0.66)
2. Studying engineering will require more effort than I'm willing to put in. (0.54)
3. For me, studying engineering may not be worth the effort. (0.67)
4. I am not sure if I've got the energy to do well in engineering. (0.78)

Psychological cost:
1. I'm concerned that I'm not a good enough student to do well in engineering. (0.72)
2. I'm concerned about being embarrassed if my work in engineering is inferior to that of my peers. (0.64)
3. I'm concerned that my self-esteem will suffer if I am unsuccessful in engineering. (0.69)
4. I worry that others will think I am a failure if I do not do well in engineering. (0.72)
5. I'm anxious that I won't be able to handle the stress that goes along with studying engineering. (0.69)