Motivation in Transition: Development and Roles of Expectancy, Task Values, and Costs in Early College Engineering

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Abstract

This longitudinal study investigated development in expectancy for success (perceived competence), three types of task value (utility, interest, attainment), and three types of perceived cost (opportunity, effort, psychological) for engineering students during their first two years of college. Latent growth curve models indicated declines in expectancy and values, with attainment value declining more slowly than expectancy, interest value, and utility value. Costs increased over time, with effort cost increasing more rapidly than psychological cost. Demographic differences were observed in initial levels of motivation, but not in rates of change over time. Students with slower declines in expectancy and value and slower increases in effort cost achieved higher grades and were more likely to remain in an engineering major. The attainment value model explained the largest amount of variance in engineering major retention, while the expectancy model explained the largest amount of variance in GPA. Taking a supportive gateway course in the first semester rather than later was associated with slower declines in utility value and attainment value, and slower increases in effort cost. Results suggest expectancy, values, and costs display unique patterns of development and uniquely relate to predictors and outcomes, extending our theoretical understanding of motivation in early college. Implications for practice include the promise of programmatic efforts to support students' motivation in engineering through supportive gateway courses early in college.

Keywords: motivation development; expectancy-value theory; STEM persistence; higher education

Educational Impact and Implications: Motivation processes provide a promising avenue for addressing attrition and representation issues in STEM fields. Yet, little is known about the development of specific forms of motivation and their correlates during the first two years of college, a key time for shaping motivational beliefs and future choices. Among college engineering students, positive motivational beliefs (expectancy for success, interest value, attainment value, and utility value) regarding engineering declined over time while negative motivational beliefs (perceived opportunity cost, effort cost, and psychological cost) increased over time. Differential rates of change for each motivation construct suggest that developmental processes differ across motivational constructs. Women did not report different trajectories than men; however, underrepresented minority students and first-generation college students reported more adaptive patterns of motivation when beginning college. Developmental trajectories of motivation constructs were significantly related to retention and grades, with expectancy most strongly predicting grades and identity-related attainment value most strongly predicting major retention. Lastly, students enrolled in a supportive gateway course in their first semester (vs. later) exhibited slower declines in attainment and utility value, and slower increases in effort cost. Results highlight the importance of supporting college students' motivation in STEM fields and of the key role of supportive gateway courses. Furthermore, differences in developmental trajectories and their relations to predictors highlight the need to understand students' specific motivational needs. Results also suggest implications for the timing and design of motivational interventions to support college student success in STEM.

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College students pursuing science, technology, engineering, and math (STEM) fields often face internal and external barriers to their success and persistence; these barriers include loss of interest, declining competence beliefs, and increased costs associated with course demands (Seymour & Hewitt, 1997). Indeed, there is clear evidence that motivation declines across levels of schooling (Fredricks & Eccles, 2002; Jacobs, Lanza, Osgood, Eccles, & Wigfield, 2002) and even within a single semester (Kosovich, Flake, & Hulleman, 2017). However, most of this research focuses on long-term declines during primary and secondary schooling. The development of STEM motivation during the first two years of college, a key transitional period for shaping choices and behaviors leading to academic and career success, is relatively understudied. Understanding changes in motivation during the early college years may be especially critical for supporting motivation, retention, and achievement in STEM fields (Perez, Cromley & Kaplan, 2014) because students tend to decide whether they will continue to pursue STEM pathways based on their early experiences in college (Jones, Paretti, Hein, & Knott, 2010; Kuh, Cruce, Shoup, Kinzie, & Gonyea, 2008). Further, given that understanding the critical role of motivation in supporting STEM persistence in college is an area of national focus (National Academies of Sciences, Engineering, and Medicine, 2016; Wang & Degol, 2013), it is important to understand how personal and contextual factors can support or undermine positive development of motivation in STEM.

Accordingly, we use contemporary Expectancy-Value Theory (Eccles et al., 1983) as a framework to investigate changes in motivation (expectancies, values, and perceived costs) among undergraduate engineering students from just before beginning college through the first two years of college and to examine predictors and outcomes of these motivation trajectories. In addition to addressing important practical questions regarding our future STEM workforce, this longitudinal study of motivational processes during early college also contributes to our theoretical understanding of how expectancies, values, and perceived costs may uniquely develop during college, how different types of motivation change over time, as well as the potentially unique roles of motivational constructs in relation to predictors and outcomes associated with initial levels and changes in motivation.

Development of Expectancy, Values, and Costs

Modern Expectancy-Value Theory (Eccles et al., 1983) posits that individual appraisals of value and expectancies for success in a task or domain are key proximal predictors of outcomes such as achievement and choice, propositions which are supported by decades of empirical research (Wigfield, Tonks, & Klauda, 2016). Expectancies refer to students' beliefs about the likelihood of future success on a task or activity, while task value is broadly defined as students' reasons for engaging in achievement-related behavior. Expectancy-value theory describes value as multifaceted (Wigfield & Cambria, 2010): individuals may value a task or domain because it is interesting or enjoyable (interest or intrinsic value), because it is useful for one's current or future goals (utility value), or because it is important to one's identity (attainment value). Another component of task value is perceived cost, defined as the perceived drawbacks of engaging in a task. Eccles and colleagues introduced three different types of perceived costs in their early work (Eccles et al., 1983): individuals may perceive a task to be costly if it prevents them from being able to participate in other valued tasks (opportunity cost), if the effort needed to be successful in the task is worthwhile (effort cost), or if high levels of negative emotions (e.g., anxiety, stress) are associated with the potential for failure at the task (psychological cost).

Extant literature on the development of expectancies and values indicates that, on average, motivation for school typically declines over time (Fredricks & Eccles, 2002; Jacobs et al., 2002; Kosovich et al., 2017). Specifically, studies document declines in math-, language arts-, and sport-related competence beliefs and values across first through twelfth grades (Fredricks & Eccles, 2002; Jacobs et al., 2002) and seventh through twelfth grades (Chouinard & Roy, 2008) as well as declines in course-related expectancies and utility value during a semester-long college psychology course (Kosovich et al., 2017). With few exceptions (e.g., Kosovich et al., 2017; Robinson, Perez, Nuttall, Roseth, & Linnenbrink-Garcia, 2018), most of these longitudinal studies on the development of motivation were conducted in primary and secondary school settings (Jacobs et al., 2002; Watt, 2004). However, the transition to college, which involves more difficult courses and competitive climates in STEM majors, can be a destabilizing force for motivation (Perez et al., 2014; Seymour & Hewitt, 1997). Specifically, social comparisons and the difficulty of tasks in introductory engineering courses may lead students to doubt their abilities; furthermore, increased academic demands and the loss of valued alternatives may lead to declining value and increasing perceptions of cost. The National Academies of Sciences, Engineering, and Medicine (2016) have identified an urgent need for research on the role of motivational constructs (including competence beliefs and values) in STEM persistence. Understanding how motivation develops as students begin college, particularly for students in STEM fields, can provide key information about how this period may be distinct with regard to development, and also about how the college environment may support or undermine motivation during the transition.

Even less is known about the development of perceived costs, as this component is rarely studied in expectancy-value research (Flake, Barron, Hulleman, McCoach, & Welsh, 2015; Wigfield & Cambria, 2010). Given that perceived costs are typically negatively related to expectancies and values (e.g., Conley, 2012; Flake et al., 2015; Trautwein et al., 2012), one may speculate that perceived costs increase over time. Barron and Hulleman (2015) reported supportive evidence for this speculation based on initial findings from a longitudinal study on middle school students' math-related expectancies, values, and costs over time. While specific measures and parameters were not reported, they found generally decreasing patterns of expectancies and values from fifth through seventh grade and increasing patterns of perceived costs during the same period. Watt (2004) also found students' perception of task difficulty (a likely correlate of perceived effort cost) in math and English increased from seventh grade to eleventh grade; however, perceptions of effort required remained relatively stable. Taken together, theory and a small amount of empirical evidence suggests that students' perceptions of cost might increase over time, but this hypothesis regarding the changes in college students' perceived costs has not been tested empirically.

In addition to the dearth of research on developmental changes in motivation during college, most research examining changes in expectancy, values, and costs has focused on a single type of value (e.g., Robinson et al., 2018; Chouinard & Roy, 2008; Kosovich et al., 2017) or combined multiple forms of value into a composite indicator (e.g., Archambault, Eccles, & Vida, 2010; Fredricks & Eccles, 2002; Jacobs et al., 2002; Musu-Gillette, Wigfield, Harring, & Eccles, 2015). Prior research indicates that different facets of value are distinct as early as fifth grade (Eccles & Wigfield, 1995; Wigfield, 1994; Wigfield et al., 2016), and some evidence suggests that expectancies and different types of value and cost have unique underlying developmental processes (Gaspard et al., 2017; Watt, 2004; Wigfield, 1994). For example, Wigfield (1994) posited that interests may become stable before utility and attainment values, which stabilize during adolescence and into early adulthood. Further, Kosovich and colleagues (2017) found that while course-related utility value and expectancy both declined across a single semester, utility value declined more slowly than expectancy (-.09 vs. -.31, with non-overlapping confidence intervals). However, no other task values were included in the study. Thus, it is important to assess whether all forms of task value and cost change at similar rates, or whether their developmental trajectories differ.

Moreover, studying the development of expectancy for success, specific task values, and costs during the early college years is important as this is a key period for students' developing academic and career-related identities (Côté, 2006; Eccles, 2009; Marcia, 1993; Roisman, Masten, Coatsworth, & Tellegen, 2004; Waterman, 1993). However, very few studies have examined the predictors of and/or stability of expectancy-value constructs during college (see Kosovich et al., 2017 and Robinson et al., 2018 for exceptions) and these few existing studies did not consider the full array of values and costs. For instance, in prior work focused on attainment value (e.g., science identity) for science students in another sample of undergraduates, Robinson et al. (2018) found that the majority of students exhibited stable trajectories of attainment value throughout four years of college. This study did not, however, examine changes in other motivation constructs, so it was not possible to examine its relative stability. No studies, to our knowledge, have compared developmental processes for expectancies, three types of value, and three types of cost during college. This research is particularly important as the extant literature provides mixed evidence about developmental patterns leading up to and immediately after the transition to college. For instance, Jacobs et al. (2002) found that declining competence beliefs appeared to level off at the end of high school, while Kosovich and colleagues (2017) found that course-related expectancies for success declined rather sharply across a semester-long introductory psychology course, suggesting that these declines also appear in college. These differences could be due to level of measurement (e.g., course-related vs. domain-related or school-related) and the time period examined. However, they could also reflect the possibility that the transition to college involves exposure to experiences that can destabilize motivation, highlighting the need to study changes in motivation during early college.

Expectancy, Values, Costs, and Academic Outcomes

There is extensive empirical evidence on the relation of expectancies and values to academic outcomes such as achievement and persistence, and some research on costs addresses these relations as well. Typically, expectancies are stronger predictors of achievement, whereas values are stronger predictors of choice (Eccles & Wigfield, 2002; Marsh et al., 2013; Perez et al., 2014). However, the pattern of findings is not always observed (e.g., Bong, 2001; Kosovich et al., 2017; Simpkins, Davis-Kean, & Eccles, 2006), particularly among older students, and may depend on the level of measurement, the domain and time period examined, and whether a cross-sectional or longitudinal approach is employed. For example, Kosovich et al. (2017) found that changes in college students' course-related expectancies, but not utility value, predicted continuing interest in psychology. Regarding costs, some evidence shows that perceived costs are negative predictors of both achievement and choice (Barron & Hulleman, 2015; Flake et al., 2015). However, Perez and colleagues (2014) found that college students' perceived costs predicted intention to leave from STEM majors but did not predict chemistry course grades. Differing patterns of relations to outcomes across studies could indicate a developmental shift in the relative salience of values, costs, and expectancies for predicting outcomes in college as compared to K-12 settings; however more research is needed to support this claim.

Further, contemporary expectancy-value theory emphasizes the unique roles played by different types of value in predicting outcomes (Eccles, 2009). A few studies on high school students indicate that rather than functioning as a unitary construct, specific values appear to differentially predict outcomes, with interest value, utility value, and/or attainment value (conceptualized as broad personal importance) displaying unique patterns of relations to outcomes such as educational attainment, course choices, major selection, and achievement (Durik, Vida, & Eccles, 2006; Eccles, Barber, & Jozefowicz, 1999; Guo et al., 2016; Guo, Marsh, Morin, Parker, & Kaur, 2015a; Guo, Parker, Marsh, & Morin, 2015b; Watt et al., 2012). However, the patterns were not consistent across studies, and it is also unclear whether these inconsistent findings are due to different research designs (e.g., different ages, different domains). For example, interest value at a single time point was a predictor of high school math course selection in a study by Guo and colleagues (2015a) but did not predict high school math course selection in a study by Watt and colleagues (2012). Similarly, interest value often predicts achievement, but these relations differ or even disappear depending on the other variables included in the model (Guo et al., 2015b; 2016).

Notably, each of the studies finding unique patterns of relations between expectancy-value constructs and outcomes outlined above examined these constructs in the same model. While it is beneficial to understand the unique relations among the variables of interest while controlling for others, collinearity and suppression issues may arise when examining multiple constructs that are highly correlated. This is a particular concern when attempting to understand similarities and differences among expectancy, task values, and costs in development and relations to outcomes. Thus, it is also important to understand the comparative predictive power of each construct to determine the most appropriate inroads for motivation interventions in education. Taking this approach, Durik, Vida, and Eccles (2006) used separate models for self-concept of ability, intrinsic value, and importance (a composite of utility value and broad importance) and found that both types of value similarly predicted course choices, but different types of value displayed unique relations to career aspirations and leisure time reading. Perez and colleagues (2014) investigated all three types of perceived cost in separate models and found that effort cost most strongly predicted intentions to stay in a STEM major. Opportunity cost also significantly predicted this outcome, but psychological cost did not. For researchers and educators aiming to promote a variety of adaptive student outcomes, it is important to understand how each type of value and cost relates to different key outcomes, thus guiding intervention efforts.

From a developmental perspective, it is clear that empirical evidence is needed to understand the relative importance of each type of motivation for predicting outcomes during college, a setting that may be unique with regard to the development of motivation and its relations to outcomes. For instance, utility value has been theorized to play an increasingly important role relative to interest value starting in middle school as students begin to seriously consider how academic activities might be useful for future careers (Wigfield & Eccles, 1989, 1992). However, more recent conceptualizations of attainment value as identity-related value (Eccles, 2009) and the salience of identity-related processes in guiding academic and professional choices in college (Eccles, 2009; Marcia, 1993; Roisman et al., 2004; Waterman, 1993) suggest that attainment value might also become increasingly important relative to interest and utility values for choice-related outcomes in college. Costs may also become increasingly important and malleable in college as students' activities increase in number, diversity, and importance for future goals (Wigfield & Eccles, 1992). Given the increasingly negative perceptions of STEM-related majors (e.g., heightened task difficulty, loss of interest) with age and highly demanding coursework in STEM majors (Seymour & Hewitt, 1997; Watt, 2006), perceived costs are expected to play a key role in academic outcomes in STEM fields. Taken together, theory and prior research suggest that expectancy, utility value, and attainment value may be the strongest predictors of major retention and achievement in college. However, it remains an open empirical question as to which constructs most strongly predict key persistence-related outcomes in college. This information is critical for effectively designing interventions to support motivation and academic success as well as for advancing our theoretical understanding of how these motivational constructs develop during early adulthood.

Lastly, while a great deal of research has examined how expectancies, values, and costs at a single time point relate to subsequent or concurrent outcomes (e.g., Battle & Wigfield, 2003; Bong, 2001; Bong, Cho, Ahn, & Kim, 2012; Guo et al., 2015a, 2015b; Perez et al., 2014), there is evidence that both the initial levels (intercepts) and rates of change (slopes) of motivation differentially predict outcomes (e.g., Kosovich et al., 2017; Musu-Gillette et al., 2015). Therefore, it is important to account for both initial levels and change over time, especially considering that students enter college with beliefs based on prior experiences and quickly encounter new and potentially destabilizing early college experiences.

Predictors of Expectancy, Value, and Cost Trajectories

Beyond considering patterns of motivational development and their relation to key academic outcomes, it is also important to understand the personal and contextual factors that predict differences in initial levels and changes in motivation to inform both our theoretical understanding of how motivation develops and the design of supports for success in college STEM programs. While expectancy, values, and costs may share some common developmental origins such as the feedback of important socializers and cross-domain comparisons, they are also assumed to have some unique relations to predictors. For example, expectancies for success are believed to be highly sensitive to students' actual successes and failures, while value and cost beliefs may be more likely to be shaped by factors such as cultural milieu, important others, and classroom activities (Eccles, 2005; Wigfield et al., 2016). Different types of value may also be socialized differently. Utility value is theorized to be the most extrinsic of the values, and so most likely to be responsive to external interventions (Harackiewicz, Canning, Tibbetts, Priniski, & Hyde, 2016; Wigfield & Eccles, 1992). Conversely, attainment value is most related to identity processes and so less likely to change in the short-term (Eccles, 2009) and less likely to respond to specific interventions. Thus, it is important to examine how predictors may relate to expectancies and each type of value and cost specifically. As we note below, some prior literature indicates that expectancy, values, and costs may develop differentially across demographic groups, leading to differences in motivation at the beginning of college, differences in rates of change over time, or both. Contextual supports, such as a supportive early college course, may also differentially predict changes in expectancy, values, and costs.

Demographic differences. Regarding gender, empirical evidence suggests that female students tend to have lower overall expectancies for success in STEM domains such as mathematics (Jacobs et al., 2002; Nagy et al., 2010; Watt, 2004; Wigfield et al., 1997; Watt et al., 2012). Value and cost have not consistently been found to vary across genders (Eccles, 2009), particularly when a composite value measure is used (Watt, 2002; Wigfield et al., 1997). However, research examining differentiated values in a variety of domains found that boys had higher interest value for math (Frenzel, Goetz, Pekrun, & Watt, 2010; Watt, 2004; Watt et al., 2012) while utility/attainment value was similar for boys and girls (Watt, 2004; Watt et al., 2012). Also, boys showed lower effort cost and psychological cost in math (Gaspard et al., 2015; Watt, 2004) whereas boys and girls showed similar levels of opportunity cost (Gaspard et al., 2015). In short, gender may be differentially related to specific value and cost beliefs. Notably, prior research also suggests that gender gaps in math-related value and competence beliefs tend to close in adolescence (Fredricks & Eccles, 2002), and one would expect that students choosing to pursue engineering at the beginning of college both value and feel confident in pursuing engineering. Thus, motivation for a math-intensive field at the beginning of college may not mirror prior findings of gender gaps during childhood or adolescence.

Regarding gender differences in the development of motivation, findings on developmental patterns are inconsistent in that some studies found no gender differences in rates of change over time (e.g., Frenzel et al., 2010; Kosovich et al, 2017; Nagy et al., 2010; Watt et al., 2012), while others observed gender differences (Chouinard & Roy, 2008; Fredricks & Eccles, 2002). Those studies finding differences reported slower declines in math ability beliefs among girls from first through twelfth grade (Fredricks & Eccles, 2002) and during seventh and ninth grade (Chouinard & Roy, 2008), suggesting gender gaps may close over time. Overall, gender findings are inconclusive and importantly, prior findings are largely focused on primary and secondary school. Consequently, gender as a predictor of the development of motivation during college is in need of further examination.

There is less empirical research examining differences in the development of expectancies, values, and costs across racial and ethnic groups or comparing first-generation college students to continuing-generation college students. However, low representation in STEM fields and lower likelihood of completing degrees in STEM (Koenig, 2009; Myers & Pavel, 2011; National Science Board, 2016; Sirin, 2005) among racial/ethnic minorities traditionally underrepresented in STEM fields (e.g., Black, Hispanic, or Native American students) and first-generation college students suggest that students from these groups may differ in their initial motivation and in changes over time. Students from underrepresented groups face additional barriers to sustaining motivation in STEM, such as discrimination (Eccles, Wong, & Peck, 2006), stereotype threat (Murphy, Steele, & Gross, 2007), belonging threat (Walton & Cohen, 2007), financial hardship (Saenz, Hurtado, Barrera, Wolf, & Yeung, 2007), or perceptions that pursuing STEM is incongruent with valued identities (Cheryan, Plaut, Davies, & Steele, 2009; Diekman, Brown, Johnston, & Clark, 2010; Settles, Jellison, & Pratt-Hyatt, 2009).

Indeed, recent research suggests that racial/ethnic majority students (White and Asian) are most likely to exhibit high and stable identity-related science attainment value throughout college as compared to students from underrepresented racial/ethnic groups (Robinson et al., 2018). However, just before beginning college, students from underrepresented groups may report higher or equivalent levels of positive motivation and lower levels of perceived cost compared to White, Asian, or continuing-generation college students because of the need for additional motivation in the face of barriers faced by these students (Fuligni, Witkow, & Garcia, 2005; Graham, 1994; Graham & Taylor, 2002; Wigfield, Cambria, & Ho, 2012). Thus, traditionally underrepresented racial and ethnic minority and first-generation students may begin college with similar levels or even more adaptive patterns of motivation compared to their peers, but may then experience more rapid changes in motivation during college.

Contextual influences on motivation. While personal characteristics play a role in shaping motivation, it is also imperative to understand how context may influence initial levels and development of expectancy, values, and costs in college. This is particularly important for programs and instructors aiming to better support academic success as students transition to college STEM fields (Cromley, Perez, & Kaplan, 2016). A growing body of research focuses on student-level interventions for supporting motivation (Lazowski & Hulleman, 2016; Rosenzweig & Wigfield, 2016); this research provides evidence that even a brief exercise can boost motivation, particularly for those most at risk for low achievement (e.g., Harackiewicz et al., 2016; Hulleman et al., 2017). Contextual factors, such as instructor practices, peers, and assessment criteria, can also play a role in shaping motivation (Ames, 1992; Jones, Audley-Piotrowski, & Kiefer, 2012; Linnenbrink-Garcia, Patall, & Pekrun, 2016). In particular, early experiences in college STEM courses can destabilize students' motivation through more difficult coursework and competitive environments (Seymour & Hewitt, 1997; Silva & White, 2013). Conversely, an introductory engineering course designed to provide support may boost motivation and retention in engineering (Lent, Brown, Schmidt, Brenner, Lyons, & Treistman, 2003).

However, little research investigates programmatic predictors of motivation development in college. Existing research on STEM motivation and persistence emphasizes the importance of students' experiences in gateway STEM courses early in college for shaping students' beliefs related to success, continuation, and motivation to pursue STEM throughout college (Cromley et al., 2016; Dai & Cromley, 2014; Gasiewski, Eagan, Garcia, Hurtado, & Chang, 2012; Perez et al., 2014). Taking a supportive course early on, particularly a course that is designed to support students' motivation and academic success, may be a key buffer against the typical declines in motivation seen as a result of competitive environments and difficult introductory "weed-out" courses (Perez et al., 2014; Seymour & Hewitt, 1997). Because declines in motivation may begin very early, it is important for students to have positive experiences that can inform their long-term motivation development. Research on how such factors shape students' motivation is particularly important for understanding how programs and policies can be developed to more effectively support students' motivation in STEM fields.

Current Study

The present study investigated trajectories of expectancies for success, three types of value, and three types of perceived cost for undergraduate engineering students across three time points during their first two years of college (just prior to beginning college, end of first-year spring semester, end of second-year spring semester). We were particularly interested in this time period as theory and prior research suggest that expectancies and some values would largely have stabilized by late adolescence (Wigfield, 1994); however, the transition to college, particularly in STEM, could be a destabilizing force for motivation. We employed academic perceived competence as an indicator of expectancies for success because competence-related beliefs are highly related to students' expectancies for success and are typically viewed by students as indistinguishable from expectancies for success (Eccles & Wigfield, 1995; Eccles & Wigfield, 2002; Wigfield & Eccles, 2000). We examined interest value, attainment (identity-related) value, and utility value for positive values, and opportunity cost, effort cost, and psychological cost for perceived cost in order to better understand unique patterns associated with these different forms of value and cost. We considered both demographic (race/ethnicity, gender, first-generation college student) and contextual factors (taking a supportive gateway course during the first semester of college) as predictors of motivational trajectories and examined how these trajectories related to retention in an engineering major and grade point average (GPA) in engineering courses at the end of the second year of college.

Our first research question concerned the nature of change in the seven motivational constructs (expectancy, interest value, attainment value, utility value, opportunity cost, effort cost, and psychological cost), including an examination of latent intercepts and whether there was significant latent change over time. The current study extends prior research by examining a two-year period at the beginning of college, by comparing development for seven distinct constructs, and by using a second-order latent growth approach, with latent motivation constructs at each time point and latent growth factors. This modeling approach, in contrast to using observed composite scores at each time point, accounts for measurement error and reduces bias in parameter estimates at the item and construct levels (Grimm & Ram, 2009).

Based on prior research finding average declines in expectancy and value and increases in cost consistently across the short- and long-term and across multiple developmental periods (Barron & Hulleman, 2015; Fredricks & Eccles, 2002; Jacobs et al., 2002; Kosovich et al., 2017), we expected expectancy and values to decline but costs to increase over time. Regarding comparative rates of change, we expected that (1) expectancy and utility value would have the most rapid change due to their theorized responsiveness to experiences and (2) attainment value would change more slowly than other constructs because it is theorized to develop slowly over long periods of time (Eccles, 2009; Robinson et al., 2018), with more moderate levels of change expected for interest value. Due to the dearth of prior research on cost development, we did not make specific hypotheses about the relative stability of costs in comparison to other motivational constructs.

Our second research question focused on understanding whether each of these motivation constructs played unique roles with respect to key outcomes in college. We examined trajectories of all seven constructs as predictors of fourth-semester GPA in engineering coursework and fourth-semester retention in engineering, two important indicators of success and persistence in engineering. Specifically, engineering GPA provides insight into whether students are progressing through coursework on the way to their engineering degree, is used to evaluate students for formal admission to engineering programs at this university, and often serves as an important factor for determining eligibility for engineering internship opportunities, employment after graduation, and graduate study. Regarding major retention, most students who leave STEM majors do so in the first two years (Griffith, 2010), so this is a particularly important time to examine motivation as predictors of major retention. Based on prior research (Eccles & Wigfield, 2002; Marsh et al., 2013; Perez et al., 2014), we predicted that the expectancy model would be the strongest predictor of engineering GPA, that the value models would be stronger predictors of major retention, and that effort cost would more strongly predict retention and GPA than other costs. Because little research has examined growth in multiple values and costs in the same study, we did not make further specific hypotheses about the potential differential strength in the relation of these constructs to persistence outcomes.

Given our interest in understanding the development of motivation in STEM fields among groups traditionally underrepresented in the field and in identifying potential interventions to support motivation and persistence in STEM fields, our third research question investigated demographic variables (gender, race/ethnicity, first-generation college student status) and the timing of a supportive gateway engineering course as predictors of initial levels (demographic variables only) and rates of change (demographics and course timing) in expectancies, values, and perceived costs. Though not a central focus of our research, we also included math ACT scores as a covariate to control for potential motivational differences across demographic groups and course timing groups as a function of prior achievement.

Empirical evidence of demographic differences in motivation specifically for engineering is scant; however, prior research in STEM and low participation rates of women, underrepresented racial/ethnic minority groups, and first-generation college students in engineering suggest that motivation trajectories might differ across these groups. Specifically, it could be that women, underrepresented racial/ethnic minority students, and first-generation college students choosing to pursue engineering would enter college with similar or even higher initial motivation compared to men, racial/ethnic majority students, or continuing-generation college students, but would be more likely to experience declines over time. In other words, due to external barriers in pursuing engineering for these groups, it may be that students from these underrepresented groups enter college with higher motivation that has thus far acted as a buffer to attrition from STEM, but that experiences in college may be more likely to destabilize those beliefs. Thus, we made tentative hypotheses that there would be some differences across these demographic groups with respect to motivation intercepts, slopes, or both.

In addition, we were interested in examining the effectiveness of a particular programmatic practice aimed at supporting students' motivation and persistence. Specifically, we tested whether taking a supportive gateway engineering course during the first semester, as recommended by the engineering program (versus after the first semester), predicted different rates of change in expectancy, values, and costs. This two-credit course was designed to promote disciplinary knowledge, persistence in engineering, and career readiness through involvement in authentic team-based engineering projects, technical writing assignments, and reflection on the roles of engineers in society. Instruction and projects focused broadly on the importance of engineering and specific skills for success in engineering careers. The course was also designed to support students by demonstrating how the content of their difficult introductory courses (e.g., chemistry, mathematics) applies to engineering practice. Course topics guided students through the design process and included project management, professionalism, creativity, ethics, and engineering careers. Thus, while the course was not designed by motivation researchers, students' motivation may have been supported through course activities. Specifically, expectancy for success may have been supported via early mastery experiences on small, low-pressure weekly individual assignments, such as computer coding and short technical writing tasks. Students' task values may have been targeted through application of engineering content to real-world situations (e.g., developing water purification systems in partnership with corporate and community entities) and in alignment with their own goals (e.g., gaining knowledge about future careers from readings and lecture). Reflection on how the efforts of engineers lead to worthwhile outcomes, as outlined in course lectures about the roles of engineers in society, may also have mitigated cost perceptions. More information about the design of the course can be found in Walton et al. (2013), Hinds, Idema, Davis-King, Buch, & Wolff (2010), and Hinds, Wolff, Buch, Idema, & Helman (2009).

Notably, we do not test whether the content itself effectively supported motivation, but rather whether the timing of course enrollment had implications for motivation development. We hypothesized that students who took this first required engineering course during their first semester in college would have more adaptive motivational trajectories during the first two years of college because they were provided extra support during a key transitional period.

Method

Participants and Procedure

Data were collected via online surveys and from university records as part of a larger study evaluating engineering programming at a large, public university. All first-year engineering majors in Fall 2015 (N = 1,317) were recruited via email and during an engineering college orientation. Seven hundred eighty-nine undergraduate engineering students provided informed consent and enrolled in the study (25.5% female; 18.6% first-generation college students; 69.8% White, 16.6% Asian/Asian American, 6.6% Black/African American, 4.1% Hispanic/Latino/a). Students completed online questionnaires in the week before their first semester of college (Time 1), near the end of their second semester of college (Time 2), and near the end of their fourth semester (Time 3). For the Time 2 and Time 3 surveys, students were contacted through program courses and via email. See missing data analysis for information about response rates across the three time points and mechanisms of missing data. The study was deemed exempt by the Institutional Review Board (IRB No. X12-375e) at the authors' institution.

Measures

Motivation. Students responded to questions about their motivational beliefs, including expectancy for success in engineering courses and task values and costs for engineering, at all three time points. All motivation items were assessed on a 5-point Likert-type scale (1 = *strongly disagree*, 5 = *strongly agree*). The full list of items is provided in the Appendix.

Expectancy for success. To measure expectancy for success in the domain of engineering, we adapted a five-item scale developed by Mamaril, Usher, Li, Economy, and Kennedy (2016; α = .83 - .89). A sample item was: "I'm certain I can earn a good grade in my engineering-related courses."

Task value. Three components of task value (attainment value, utility value, interest value) were assessed using scales adapted from Conley (2012) and Pugh, Linnenbrink-Garcia, Koskey, Stewart, and Manzey (2009). Specifically, interest value assessed students' feelings of enjoyment related to engineering (5 items; α = .87 - .92, sample item: "Engineering is exciting to me"). The attainment value scale measured the importance of engineering to students' identity using four items (α = .76 - .84, sample item: "Being involved in engineering is a key part of who I am"). Finally, the utility value scale included four items measuring the degree to which students found engineering useful for their current or future goals α = .77 - .89, sample item: "Engineering will be useful for me later in life").

Perceived cost. Three types of cost (opportunity, effort, psychological) were measured using scales adapted from Perez et al. (2014). The opportunity cost scale (3 items, α = .79 - .87) asked students about their perceptions of the loss of valued alternatives in pursuing engineering (sample item: "I'm concerned that I have to give up a lot to do well in engineering"). Effort cost (4 items, α = .74 - .81) assessed students' perceptions of the effort required to be successful in engineering (sample item: "For me, studying engineering may not be worth the effort"). Psychological cost (5 items, α = .83 - .84) measured students' concerns about the emotional consequences of failure in engineering (sample item: "I'm concerned that my self-esteem will suffer if I am unsuccessful in engineering").

Confirmatory factor analysis. To assess whether participants viewed expectancy, the three types of value, and the three types of cost as distinct constructs, we conducted a confirmatory factor analysis

(CFA) for each time point including the seven latent constructs, correlating all constructs with each other. The seven-construct CFA showed acceptable fit at T1, χ^2 (384) = 1158.20, CFI = .92, RMSEA = .05, T2, χ^2 (384) = 974.65, CFI = .93, RMSEA = .06, and T3, χ^2 (384) = 1090.45, CFI = .91, RMSEA = .06, supporting the conceptual and statistical differentiation of expectancy, three task values, and three types of cost across all three time points. Tests of measurement invariance over time are presented in the results section.

Gateway course timing. Information about students' enrollment in a required, supportive gateway engineering course (1 = *took the course in their first semester* and 0 = *took the course after the first semester*) was attained from institutional record data. Students were encouraged to take this introductory course in their first semester; however, some students chose to delay. Others encountered barriers to enrollment in the course due to later registration times and/or later admission to the university for those with lower achievement or those who delayed paying an admission deposit. Lastly, some students (n = 43) were ineligible to take the course in the first semester due to low scores on mathematics placement exams, and others did not enroll in the course during their first four semesters (n = 79, 14 of whom were also ineligible to take the course in the first semester). In the conditional models we excluded those who were ineligible to take the course in the first semester and/or did not enroll in the course during the first four semesters. We also controlled for ACT Mathematics scores and demographic variables to account for later admission and registration as reasons for taking the course after the first semester. A total of 676 students were included in this analysis, as they were eligible to take the course in the first semester and took the course during their first, second, third, or fourth semester.

Prior achievement. Students' scores on the math section of the ACT exam were obtained from university records as an indicator of prior achievement. Mathematics achievement was a key prerequisite for enrollment in introductory engineering courses, and the mathematics section of the ACT has been shown to have high predictive validity for college outcomes compared to other subsections of the ACT

(Bettinger Evans, & Pope, 2013). Reliability estimates (r_t) for the sub-scales within the 60-item mathematics ACT ranged from .90 - .92 (ACT, 2017)[1]. Math ACT scores were standardized.

Demographic variables. We examined institutional record data and survey data to obtain demographic information, including gender (1 = female, 0 = male), first-generation college student status (1 = parents did not attend college, 0 = parents attended college or higher), and race/ethnicity. Due to low numbers of students indicating specific racial/ethnic minority groups, categories were collapsed into a dichotomous variable indicating membership in a racial or ethnic group that is traditionally underrepresented in engineering (Black or African American, Hispanic/Latino, Native American, or Pacific Islander), with 1 = underrepresented racial/ethnic minority (11% of the sample), 0 = racial/ethnic majority (89% of the sample).

Dependent variables. Retention in an engineering major at the end of students' fourth semester of college (1 = engineering major, 0 = non-engineering major) and GPA in fourth-semester engineering courses were obtained from institutional records. Engineering courses were considered to be courses listed on major requirements for any engineering major at the university, including selective courses, and largely consisted of courses offered by the engineering college, but also included pre-requisite courses in domains such as mathematics, chemistry, and biology. At this university, students declare an anticipated major before beginning their studies; however, they are not formally evaluated for admission into the College of Engineering until they complete 56 total university credits. This typically occurs just after the fourth semester and is based on performance in engineering and pre-requisite mathematics and science courses. Because we used fourth semester major as an indicator of retention, the vast majority[2] of those listed in our data as non-engineering majors voluntarily left the major before or during the fourth

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[1] Reliability estimates were obtained from the 2017 ACT Manual, which used data from 2015-2016 ACT results. Although we do not have information about the specific time each participant completed the ACT, the ACT website (https://www.princetonreview.com/college/act-changes#!tab2) indicates that the format and content of the math ACT exam has not changed substantively within the time our participants would have taken the ACT.

[2] Fifteen participants from our sample left engineering after receiving an unsatisfactory admission evaluation. Ancillary analyses involving the dependent variables were also conducted without these 15 individuals and the results remained consistent; thus we retained these 15 individuals in our final sample to more fully reflect the initial population of engineering majors.

semester. Thus, our conceptualization of retention reflects major choice rather than formal admission to an engineering program.

Analytic Plan

Preliminary analyses included an examination of missing data patterns and longitudinal factor analyses for testing measurement invariance of each factor across time. Main analyses consisted of (1) a series of second-order latent growth curve analyses for testing two-year trajectories of each construct,[3] and (2) conditional latent growth models including predictors and outcomes. Fit was determined via the Comparative Fit Index (CFI; values >= .90 for adequate fit; values >= .95 for excellent fit; Hu & Bentler, 1999) and root mean square error of approximation (RMSEA; values < .08 for adequate fit; values < .06 for excellent fit). Motivation variables were treated as continuous, which is recommended when items have five or more categories and are approximately normal (Beauducel & Herzberg, 2006; DiStefano, 2002; Dolan, 1994; Johnson & Creech, 1983; Muthén & Kaplan, 1985; Rhemtulla, Brosseau-Liard, & Savalei, 2012; Sass, Schmitt, & Marsh, 2014). Missing data analyses and correlations were conducted in SPSS version 22, and the remaining analyses were conducted in Mplus Version 8 (Muthén & Muthén, 1998-2017) using full information maximum likelihood (FIML) estimation to handle missing data.

Results

Preliminary Analyses

Missing data analysis. The sampling frame for the current study consisted of 789 students who completed the Time 1 survey. According to aggregate statistics obtained from the engineering college, the gender, first-generation college student status, and average Math ACT score distributions for the study sample were similar to those in the overall population of first-year engineering majors that year. Specifically, the population of first-year engineering majors for Fall 2015 was 25.6% female (compared

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[3] We were originally also interested in examining parallel growth processes for the motivation constructs; however, when attempting to model two or more constructs together, we encountered collinearity issues that led to uninterpretable model results, with non-positive definite covariance matrices and estimated correlations close to or above 1 that were not resolvable through reasonable troubleshooting methods. Thus, we were not able to pursue this line of analysis.

to 25.5% female in the present study) and 19.7% first generation college students (18.6% in the present study). The population had an average Math ACT score of 27.93 (*S.E.* = .12), which was not significantly different from the mean Math ACT score of the study sample ($M = 28.45$, *S.E.* = .16).

In subsequent survey waves, 495 students from our Time 1 sample completed the T2 survey and 445 completed the T3 survey. Students who did not complete the T2 survey were still invited to take the T3 survey, and 96 students took the T3 survey after not completing the T2 survey. Missing data due to not taking a survey or not completing particular items ranged from 0 – 48.3% at the item level, with an average missing rate of 30.0%. Missing data at T1 was negligible, with an average missing rate of 3.3% at the item level. Little's MCAR test was significant, χ^2 (6759) = 7570.38, $p < .001$, providing some evidence that the data was not missing completely at random. Therefore, the mechanism of missing data was explored by comparing T1 motivation means, demographics, and major status for those missing motivation variables at T2 or T3.

A Multivariate Analysis of Variance (MANOVA) was conducted to examine differences in T1 composite scores for engineering expectancy, values, and costs comparing individuals missing any composite scores for T2 or T3 motivation variables to participants with complete T2 and T3 data. The overall MANOVA was significant, Wilks' λ (7, 716) = 0.972, $p = .005$, $\eta^2 = 0.03$. Post-hoc examination of specific variables indicated that those with missing data significantly differed only on T1 effort cost from those with complete data, F (1, 722) = 9.45, $p = .002$, $\eta^2 = 0.01$. Chi square analyses indicated that membership in an underrepresented racial/ethnic minority group (URM) was not a significant predictor of missing data, χ^2 (1) = 3.50, $p = .06$, $\varphi = .07$, but gender, χ^2 (1) = 18.04, $p < .001$, $\varphi = -.15$, first-generation college student status, χ^2 (1) = 8.21, $p = .004$, $\varphi = .10$, and fourth-semester major status, χ^2 (1) = 53.96, $p < .001$, $\varphi = -.27$, were associated with missing data such that women, continuing-generation college students, and students who remained in an engineering major after their first two years were more likely to have complete data. Gender, first-generation college student status, and major status were included in the final, conditional models and thus assisted in FIML estimation to reduce potential bias due to missing data.

Descriptive statistics and bivariate correlations. Table 1 presents correlations and descriptive statistics for the motivation variables. As expected, values and expectancy were positively correlated at all time points, while repeated measures of cost were positively correlated with one another, and negatively correlated with expectancy and values at some time points. In general, means for expectancy and values appeared to decrease slightly over time, while costs appeared to increase. Descriptive statistics for predictors and outcomes, and correlations between motivation variables, predictors, and outcomes are presented in Table 2. Regarding course enrollment and retention, 65% of participants (n = 458) enrolled in the supportive gateway course during the first semester, and 25% of the sample (n = 189) had changed out of an engineering major by the end of the fourth semester.

Measurement invariance. Confirmatory factor analyses presented in the method section provided evidence that expectancy, values, and costs represented distinct constructs. However, for longitudinal research, it is also necessary to establish that the same construct is being measured over time (e.g., measurement invariance). Establishing measurement invariance allows one to infer that observed change over time can be attributed to true change rather than change in the meaning of the construct over time (Widaman & Reise, 1997; Widaman, Ferrer, & Conger, 2010). Measurement invariance over three time points for each first-order common factor model was evaluated by successively fitting configural, weak, strong, and strict invariance models (Table 3). The configural model constrained the factor structure to be the same across time. Weak invariance was specified by additionally constraining factor loadings to be equal across time, and strong invariance additionally assumed equal observed intercepts over time. Lastly, the strict invariance model constrained residual variances for observed factor indicators over time. Model comparisons for expectancy, interest value, attainment value, utility value, and opportunity cost resulted in a change in CFI that was less than or equal to .01 between models (Cheung & Rensvold, 2002; see Table 3), supporting strict measurement invariance over time for these constructs. For effort cost, strong measurement invariance was supported, with a reduction in CFI that was greater than .01 between the strong and strict models. Partial strict measurement invariance was supported for psychological cost, with the intercept of one T1 item allowed to freely estimate (see Table 3).

Unconditional Growth Models

To address our first research question, we compared intercept-only and linear unconditional latent growth models to determine which best represented the average pattern of change in each motivational variable for the sample. Second-order models were specified with both latent growth factors and latent factors of motivation at each time point to minimize bias by accounting for measurement error. Quadratic change can only be examined with four time points or greater, therefore we examined only intercept-only and linear models.

Overall, intercept-only models showed adequate, but not excellent, fit (CFI values = .899 to .943; RMSEA values = .058 to .069, see Table 4). Linear growth models across all seven motivational variables appeared to show better fit (CFI values = .909 to .975; RMSEA values = .047 to .055, see Table 4), with intercepts and slopes that were significantly different from zero for all models. Therefore, the linear models were selected. For psychological cost, although the intercept-only and linear models appeared to fit similarly, the linear model was selected because of the significant linear slope (see Table 5). Parameter estimates for the linear models are presented in Table 5, and model-implied trajectories are presented in Figure 1. On average, students reported moderate to high levels of expectancy and task values just before beginning their engineering studies, but these motivational variables decreased over the first two years of college, as indicated by the significant negative slopes in all four models. Cost models indicated that on average, students beginning college reported low to moderate levels of cost that increased significantly over the two-year period.

In addition, non-overlapping confidence intervals for slopes indicated that attainment value, 95% CI [-.085, -.007], declined more slowly than expectancy, 95% CI [-.174, -.104], interest value, 95% CI [-.157, -.091], and utility value, 95% CI [-.161, -.095], which did not significantly differ from one another in slope. Confidence intervals for the slopes of cost variables indicated that effort cost, 95% CI [0.13, 0.23], increased more rapidly than psychological cost, 95% CI [0.01, 0.09], but the slope of opportunity cost, 95% CI [0.04, 0.14], did not differ significantly from the other cost slopes. The variances of intercepts for all motivational variables in engineering were significant (see Table 5), meaning that students varied in their initial levels of expectancy, values, and costs. With the exception of opportunity cost and psychological cost, there was also significant variance in the slopes of all motivation constructs. Non-significant variances for the slopes of opportunity and psychological costs indicate that when controlling for initial levels of cost, individual differences in slope were not significantly different from zero. The intercept and slope of expectancy were positively correlated (see Table 5), indicating that higher levels of engineering expectancy before the first semester of college were associated with less dramatic declines in expectancy over time. The initial levels and slopes were not significantly correlated for the three task values or the three costs.

Conditional Growth Models

For our second and third research questions regarding correlates of the development of motivation, we next added predictors and outcomes to the latent growth models. Due to the very small, non-significant variances in the slopes of opportunity cost and psychological cost, we did not move forward with conditional models for these constructs, as there was no variance in slopes to be explained by predictors or to explain variance in outcomes. Therefore, conditional models consisted of expectancy, interest value, attainment value, utility value, and effort cost. For each motivation construct, predictors and outcomes were added to the model in the same step. Gender, race/ethnicity (URM), and first-generation college student status were modeled as predictors of both the intercepts and slopes. Math ACT scores were also included as a control variable predicting intercepts and slopes. Because students took the gateway engineering course after the first survey, gateway course timing was modeled as a predictor of slope only (see Figure 2). Engineering major retention and GPA in engineering courses were modeled as outcomes of the intercept and slope for each construct. All five models fit the data adequately according to RMSEA (Table 6); however, the CFIs for attainment value and effort cost were sub-optimal. Unstandardized and standardized parameter estimates for predictors of slopes and intercepts are reported in Table 7, and for outcomes of slopes and intercepts in Table 8.

Predictors of expectancy and value trajectories. Regarding demographic predictors, race/ethnicity (URM) was positively and significantly associated with the initial level of engineering expectancy, interest value, and attainment value, but not utility value when controlling for prior achievement and other demographic predictors. Race/ethnicity was significantly and negatively associated with the intercept of effort cost. Linear slope was not significantly associated with URM group membership in any of the models. These findings indicate that URM students reported higher expectancy for success, interest value, and attainment value, with lower effort cost before their first semester in college, but did not differ from White and Asian students in initial levels of utility value or in slope for any of the five constructs. In other words, URM students exhibited patterns of change in motivation that were not significantly different than the patterns of change reported by racial/ethnic majority students in engineering.

First-generation college student status positively predicted initial levels of engineering expectancy and interest value, such that students whose parents did not attend college reported higher expectancy and interest value before their first semester of college compared to continuing-generation college students. First-generation status did not significantly predict the intercepts of other variables and was also not a significant predictor of slope for any of the motivation constructs[4], indicating that first-generation college students did not significantly differ from continuing-generation college students with regard to initial utility value, effort cost, or change in all forms of motivation.

Gender was not a significant predictor of intercepts or slopes in all five models. This indicates that when controlling for race/ethnicity, first-generation college student status, and prior achievement, women in engineering did not differ from men in their motivational trajectories.

Enrollment in the required introductory engineering course in the first semester rather than later in college was positively and significantly associated with the slope of utility value and attainment value, but not expectancy or interest value (see Table 7). In other words, students who took the gateway course in the first semester reported slower declines in engineering-related utility value and attainment value

[4] While the unstandardized coefficient for first-generation college student status predicting attainment value intercept and slope were significant, the standardized coefficients were not significant and so we do not consider these findings to be robust.

throughout the first two years of college compared to those who were eligible to take the course in the first semester but opted to take the required course later. Course timing was also significantly and negatively associated with the slope of effort cost such that students who took the course in their first semester had slower increases in effort cost.

Relations to retention and GPA. The intercept of attainment value significantly and positively predicted retention in an engineering major. No other intercepts were significantly associated with retention.[5] Changes (slope) in all motivation constructs significantly predicted retention in engineering. Odds ratios based on standardized coefficients can be interpreted as the difference in odds of being in an engineering major associated with a one-standard deviation difference in slope or intercept. Thus, students with initial levels of attainment value that were one standard deviation above the mean were 1.3 times more likely to be in an engineering major at the end of their second year compared to students with mean levels of attainment value. Further, controlling for initial levels of motivation, students who reported rates of change that were one standard deviation above the mean (i.e., slower rates of decline) in expectancy and values were 1.5 – 1.9 times more likely to be engineering majors at the end of their second year compared to those with slopes at the mean. Students with slopes that were one standard deviation above the mean (i.e., faster increases) in effort costs were 31% less likely to be engineering majors compared to students at the mean.

Contrary to expectations for grades, intercepts of interest value and utility value negatively predicted fourth semester GPA, while the intercepts of other constructs were not significantly related to GPA[6]. In other words, higher interest value and utility value for engineering just before beginning college were associated with lower fourth-semester GPA, controlling for the slope of motivation, demographics, and prior achievement. The slopes of all constructs were significant predictors of GPA, suggesting that

[5] The unstandardized coefficient for the intercept of effort cost predicting retention was significant, however the standardized coefficient was not significant, so we do not consider this finding to be robust.
[6] While the standardized coefficient for expectancy intercept predicting GPA was significant, the unstandardized coefficient was not significant and so we do not consider this finding to be robust.

slower declines in expectancy for success and task values, and slower increases in effort cost, positively predicted engineering grades in the fourth semester of college.

Examining *r*-squared values for each model (Table 9) revealed that the interest, attainment, and utility value models explained a large amount of variance in engineering major retention, while the expectancy and effort cost models explained a moderate amount of variance in retention. Pairwise comparisons of *r*-squared values for retention using Fisher *r*-to-*Z* transformations (Lee & Preacher, 2013; see Table 9) indicated that the attainment value model explained significantly more variance in retention than the other models. The interest and utility value models both explained more variance in retention than the expectancy and effort cost models, but did not differ significantly from each other. The expectancy and effort cost models explained significantly less variance in engineering major retention than the other models and did not differ significantly from one another in variance explained.

With regard to grades, each of the models explained a large amount of variance in GPA (r^2 = .33-.57). Comparisons of variance explained using Fisher *r*-to-*Z* transformed values indicated that the expectancy model explained significantly more variance in GPA than all of the other models, which did not differ significantly from one another in GPA variance explained.

Discussion

The present study examined the development of expectancy for success, interest value, attainment value, utility value, opportunity cost, effort cost, and psychological cost in engineering during the first two years of college, along with demographic and behavioral correlates of motivational trajectories. We found that though students reported moderate to high expectancy and values just before beginning college, these forms of motivation declined, on average, throughout the first two years of college. Costs followed the opposite pattern, with students reporting low to moderate initial levels that then increased during the first two years of college. This is consistent with prior findings that, among secondary students and undergraduates, positive motivational beliefs tend to gradually decline over time (Anderman & Midgley, 1997; Fredricks & Eccles, 2002; Jacobs et al., 2002; Kosovich et al., 2017) while perceived costs may increase (Barron & Hulleman, 2015). However, our findings about the relative stability of expectancy-value constructs extend prior research, particularly through our focus on the first two years of college and by examining three differentiated values and three differentiated costs.

Development of Motivation

Our finding that attainment value appeared to decline more slowly than other constructs suggests that, in line with our hypotheses and prior research in other contexts (Gaspard et al., 2017; Kosovich et al., 2017; Watt, 2004), expectancies and specific task values may differ in how they develop during early college. The relative stability in attainment value also aligns with theoretical expectations (Eccles, 2009) and prior empirical evidence (Robinson et al., 2018) suggesting identity-related value is relatively stable during college. However, our specific pattern of findings differed somewhat from Kosovich et al. (2017), who found that course-related expectancies declined more rapidly than utility value for the course, perhaps reflecting differences in course-related motivation processes versus the domain-related motivation processes we examined in our study.

We also found that effort cost increased more quickly than psychological cost, but that the slope of opportunity cost was not significantly different from the slopes of effort or psychological cost. This represents the first empirical evidence that there may be differential developmental processes at work shaping different types of cost. Specifically, effort cost may be uniquely sensitive to high demands in STEM college coursework, and thus may be particularly likely to shift during the transition to college. Students' relatively rapidly increasing perceptions of effort cost may reflect their day-to-day experiences of coursework requiring high effort combined with decreasing value beliefs, resulting in increasingly salient perceptions that the high effort required to succeed in engineering is less worthwhile. In comparison, the relatively stable pattern of psychological cost may indicate that students' worries about the emotional costs of potential failure are not subject to rapid change processes. In other words, while students might reassess whether the discipline is worth the effort and time commitment that it demands in order for them to be successful, their perception of the negative emotions that would accompany failure develop more slowly.

Overall, the pattern of results suggests that interventions during the first two years of college may be most effectively aimed toward boosting utility value, interest value, or expectancy for success on academic tasks in engineering rather than attempting to shift attainment value, which remains relatively stable. Interventions to mitigate increases in effort cost may also be more effective than targeting psychological cost. It may also be that interventions to support psychological cost or identity development (i.e., attainment value) are best administered before college, as many beliefs about STEM fields are shaped and even stabilized before college, leading to attrition from STEM fields before arrival at college (Moakler & Kim, 2014; Morgan, Farkas, Hillemeier, & Maczuga, 2016; Wang, 2013; Wigfield, 1994).

It is also interesting to consider that the covariances between intercepts and slopes were not significant for any of the values or costs, indicating that initial levels of value and cost were not associated with rates of change in these variables over time. This is a promising finding with regard to implications for intervention, as it suggests that lower or higher initial levels of value may not serve as a risk factor for declines, and values may be amenable to intervention throughout the first two years of college. For expectancy, the significant covariance between intercept and slope could be an indicator that strong competence beliefs at the beginning of college can serve as a buffer against experiences that would otherwise destabilize expectancies for success in engineering, such as stereotype threat or low achievement in challenging introductory STEM courses. With regard to practice, this finding suggests that expectancy for success in engineering may best be supported before the beginning of college.

Relations to Outcomes

As expected, our results suggest that expectancies, values, and costs are important predictors of GPA and retention. First, the slopes of all five constructs examined were strongly related to both grades and engineering retention, while relations to intercepts were more complex. This suggests that changes in motivation over time, regardless of initial levels, are key predictors of choice and grades, thus underscoring the importance of understanding how to support beneficial trajectories in motivation over time for all students. Indeed, it is particularly important to mitigate declines in expectancy to support grades, and to prevent declines in attainment value to support retention outcomes, as changes (rather than initial levels) were key predictors of unique academic outcomes. Second, our findings regarding the relative strength of each value for predicting outcomes as indicated by r-squared comparisons, as well as the unique relations of intercepts and slopes to outcomes, add increased understanding of the unique roles of three types of task value. In combination with the findings regarding covariances between intercepts and slopes, this presents an optimistic view of the potential for interventions to support academic outcomes, even for students entering college with lower motivation.

Surprisingly, lower initial levels of expectancy, interest value, and utility value were associated with higher fourth-semester GPA. Low and largely non-significant correlations between intercepts and slopes along with the parallel negative bivariate correlations between initial levels of interest value and utility value with GPA suggest that these relations do not emerge as a result of suppression, but rather are true relations. These findings would suggest that to promote high grades in college courses, buffering declines is much more important than supporting high initial levels of interest and utility value at the beginning of college. Indeed, our findings may suggest that particularly high initial expectancy, interest value, and utility value could indicate a poorly calibrated sense of one's motivation to exert effort on difficult schoolwork.

The attainment value model emerged as the strongest predictor of retention in engineering majors. This runs contrary to the theoretical expectation that utility value would play an increasingly important role relative to the other values (Wigfield & Eccles, 1989, 1992). This may also reflect a change in the measurement of identity-focused attainment value, in contrast with earlier conceptualizations of attainment value as broad importance. Our findings affirm theoretical expectations regarding the salience of identity-related motivation during college (Eccles, 2009; Marcia, 1993; Roisman et al., 2004; Waterman, 1993), with both intercept and slope playing important roles in predicting retention. While interventions targeting utility value have been fruitful, and our findings suggest that attainment value in particular may not be as responsive to intervention as other constructs, future research is needed to explore whether other values may be responsive to interventions, both before and during college. These findings regarding the relative importance of each construct for predicting retention support our hypotheses and prior research indicating that values would be stronger predictors of retention compared to expectancy. Indeed, the expectancy model explained significantly less variance in retention than any of the forms of value, suggesting that when students consider whether or not to change majors, their values are more salient to that choice than expectancies for success, in line with prior research (Eccles & Wigfield, 2002; Marsh et al., 2013; Perez et al., 2014). Notably, the effort cost model also explained significantly less variance in outcomes than the three task value models, suggesting that, while reducing effort cost is beneficial, interventions might yield more success if they focused on enhancing values rather than reducing perceived costs.

With regard to grades, the finding that expectancy explained the largest amount of variance in fourth semester GPA aligns with prior research examining expectancy and value in the same model (e.g., Eccles & Wigfield, 2002; Marsh, et al., 2013; Perez et al., 2014), suggesting that expectancies are stronger predictors of achievement than values. Our approach of using separate models, however, indicates that both values and expectancies could be appropriately targeted for boosting students' grades, as values were strong predictors of grades. These findings could reflect our approach of using separate models to examine each motivation construct, whereas prior work comparing the predictive power of expectancies and values has typically examined them both in the same model (Eccles & Wigfield, 2002; Marsh, et al., 2013; Perez et al., 2014). Indeed, Trautwein et al. (2012) found that the significant relations of attainment and intrinsic value to English achievement became non-significant when expectancies were added to the models, though it is notable that utility value was still significantly related to achievement even when expectancies were included. In addition to examining each variable in separate models as we have done, it is important for complementary research to examine unique relations to outcomes when controlling for other constructs (e.g., Kosovich et al., 2017), and to examine how motivation variables function together within individuals to relate to outcomes (e.g., Linnenbrink-Garcia & Wormington, 2017; Nagengast et al., 2011).

Predictors of Motivation Trajectories

Our findings regarding predictors of motivational trajectories support the proposition that the developmental differences in values and expectancies may at least be partially explained by both internal developmental processes and the educational context (Fredricks & Eccles, 2002; Jacobs et al., 2002). Notably, we found that racial/ethnic minority students and first-generation college students entered college with higher initial levels of engineering expectancy and interest value. Underrepresented racial/ethnic minority students also reported lower initial effort cost. This finding is consistent with other research showing that Black and Hispanic students typically report higher or equivalent levels of motivation compared to White or Asian students (Fuligni et al., 2005; Graham, 1994; Graham & Taylor, 2002; Wigfield et al., 2012). Within the context of an engineering program, mean differences could also point to the particular barriers faced by underrepresented minority and first-generation college students pursuing STEM fields, indicating that these students must be particularly motivated to pursue engineering when faced with such phenomena as stereotype threat (Murphy et al., 2007), belonging threat (Walton & Cohen, 2007), or identity interference (Cheryan et al., 2009; Diekman et al., 2010; Settles et al., 2009). However, contrary to our hypotheses, there were no significant differences based on race/ethnicity and first-generation college attendance status in the slopes of expectancies and values when controlling for initial differences.

Surprisingly, we did not find evidence of gender differences in intercepts or slopes, perhaps suggesting that gender does not play the most salient role in predicting motivational trajectories in engineering when also accounting for race/ethnicity, first-generation college student status, and prior achievement. This supports a “gender egalitarian” view of the development of motivation, also supported by prior research which found that gender gaps in math value and competence beliefs narrowed in adolescence (Fredricks & Eccles, 2002).

Lastly, we found that taking a required supportive gateway course in the first semester buffered students from declines in utility value, declines in attainment value, and increases in effort cost. Students who took the course in their second, third, or fourth semester experienced more rapid changes in these constructs compared to those who took the course in the first semester. This finding suggests that there may be multiple elements of motivation that are shaped by environmental cues. It is important for future intervention research to build on the success of utility-value interventions (e.g., Harackiewicz et al., 2016) to examine whether other forms of motivation can be supported through easily modifiable programmatic efforts. With regard to practice, this finding is a promising affirmation that the programmatic efforts to support students' motivation (and ultimately their achievement and persistence) in engineering through course design and encouraging students to enroll in the first semester are helpful for buffering declines in value and increases in perceived effort cost. In other words, it is key to provide organized support in a timely manner to engineering (or STEM) students who are transitioning to college and exploring their specialized area. However, course timing did not impact declines in interest value or expectancy, suggesting that these constructs could be an area of focus for further development of the motivational supports for incoming engineering students.

Limitations and Future Directions

Our focus on the first two years of college reflects the importance of this period of transition for student success, particularly when the majority of students who drop out of engineering do so in the first two years (Griffith, 2010). However, a consideration of longer-term outcomes such as graduation and career outcomes would extend this research to inform knowledge about motivation and outcomes throughout and after college. Such research is of utmost importance for addressing the "leaky pipeline" phenomenon in STEM, and particularly the underrepresentation of racial/ethnic minority students in STEM fields.

A second potential limitation was our reliance on GPA in engineering coursework rather than a validated knowledge test. Although we acknowledge that grades are not always reliable indicators of knowledge acquisition or future success, we contend that they are appropriate for studying STEM persistence as they provide evidence of academic advancement in college and have high stakes for students' ability to pursue further academic and career opportunities.

A third potential limitation to the current study was that more than one-third of the sample was missing motivation measures for at least one time point. A challenge with conducting research in post-secondary settings is that one cannot easily access students in their classes and thus higher rates of missing data are expected in this population. However, a strength of our approach is that we were able to obtain a fairly representative sample of undergraduate engineering majors at this research university. Moreover, by using FIML and including demographic variables that were correlates of missing data patterns in the data, we were able to reduce potential bias due to missing data in our longitudinal analyses.

Fourth, our findings relating demographic variables to motivation intercepts provide some key information regarding developmental differences for groups that are minoritized in engineering fields. However, much more information is needed to better understand these processes before and during college, such as stereotype threat (Murphy et al., 2007), belonging threat (Walton & Cohen, 2007), or identity interference (Cheryan, et al., 2009; Diekman et al., 2010; Settles et al., 2009), that may lead to these differences, and to students opting out of STEM fields before entering college.

Lastly, our examination of course timing as a predictor of motivation trajectories provides an important initial test of this program's recommendation that students take a supportive gateway course in the first semester rather than later, controlling for potential confounding factors. However, to make strong causal inferences about the effects of this practice, our findings must be complemented with research using an experimental design. Furthermore, it is important to more closely examine the mechanisms whereby this course supports utility value and attainment value, perhaps through specific motivationally supportive practices within the class. More broadly, it is also important to recognize that our findings in engineering may not generalize to other STEM fields or to other settings where admissions procedures and programming may vary widely, so replication in other settings is necessary. Such research could inform further development efforts to support diverse student populations along a wider array of motivation constructs.

Conclusion

Supporting students' motivation to succeed in STEM fields is a national concern (National Academies of Sciences, Engineering, and Medicine, 2016), and for good reason. We found evidence of average declines in engineering students' expectancies for success, interest value, attainment value, and utility value throughout the first two years of college. Students also exhibited increases in opportunity cost, effort cost, and psychological cost. Relations to demographic characteristics provide evidence that can be used in the design of more equitable learning environments that can support diverse motivational needs. Further, results indicate that changes in motivation are key predictors of important outcomes, as students who maintained higher expectancy and value and lower effort cost showed higher grades and a greater likelihood of staying in an engineering major. Buffering declines in attainment value during college may be especially beneficial for promoting retention. Supports for attainment value before college rather than during college may potentially be more effective, as initial levels of attainment value predicted retention and attainment value remained relatively stable during college. For grades, buffering declines in expectancy for success during college may be most effective. Lastly, taking a supportive gateway course in the first semester was associated with slower declines in utility value and attainment value, and slower increases in effort cost, suggesting that the first semester is a key period for supporting or undermining students' perceptions of the value and relative costs associated with engineering. These results extend our theoretical understanding of expectancy, task values, and costs in college by examining changes and relative stability for differentiated motivation constructs. This study also lends support for the practicality of programmatic interventions to support motivation, and suggests a need for research examining how supports for multiple motivation constructs may promote both retention and GPA in college STEM fields.

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Table 1.

Estimated Correlations and Descriptive Statistics for Motivation Variables

	EXP1	EXP2	EXP3	INT1	INT2	INT3	ATT1	ATT2	ATT3	UTL1	UTL2	UTL3	OPP1	OPP2	OPP3	EFF1	EFF2	EFF3	PSY1	PSY2	PSY3
EXP1	-																				
EXP2	.40***	-																			
EXP3	.31***	.47***	-																		
INT1	.54***	.29***	.21***	-																	
INT2	.27***	.63***	.31***	.45***	-																
INT3	.19***	.26***	.55***	.31***	.55***	-															
ATT1	.51***	.25***	.21***	.69***	.35***	.24***	-														
ATT2	.28***	.60***	.38**	.39***	.72***	.40***	.44***	-													
ATT3	.15**	.27***	.53***	.27***	.43***	.77***	.32***	.49***	-												
UTL1	.40***	.22***	.10*	.55***	.24***	.17**	.52***	.22***	.16**	-											
UTL2	.14**	.48***	.22***	.24***	.67***	.30***	.16***	.60***	.35***	.28***	-										
UTL3	.10	.20***	.44***	.20***	.32***	.63***	.16**	.35***	.70***	.24***	.40***	-									
OPP1	-.19***	-.14**	-.01	-.11**	-.09*	-.04	-.04	-.10*	.02	-.03	-.002	-.01	-								
OPP2	-.14**	-.15**	-.11*	-.05	-.13**	-.11*	-.03	-.09*	-.05	-.02	-.04	-.10	.42***	-							
OPP3	-.18***	-.20***	-.09	-.01	-.16**	-.06	.01	-.08	.02	.03	-.09	-.05	.40***	.51***	-						
EFF1	-.32***	-.24***	-.10*	-.30***	-.23***	-.16**	-.18***	-.20***	-.11*	-.24***	-.20***	-.17**	.50***	.30***	.26***	-					
EFF2	-.17***	-.34***	-.28***	-.12*	-.34***	-.24***	-.06	-.22***	-.21***	-.10*	-.27***	-.30***	.24***	.51***	.32***	.46***	-				
EFF3	-.16**	-.28***	-.30***	-.03	-.24***	-.33***	.002	-.22***	-.23***	-.08	-.28***	-.31***	.19***	.37***	.55***	.32***	.51***	-			
PSY1	-.28***	-.19***	-.20***	-.13***	-.10*	-.11*	-.08*	-.13**	-.06	.02	.003	-.05	.54***	.32**	.24***	.44***	.21***	.19***	-		
PSY2	-.18***	-.17***	-.24***	-.09	-.04	-.17**	-.02	.04	-.04	.06	.08	-.10	.29***	.51***	.30***	.23***	.49***	.27***	.48***	-	
PSY3	-.22***	-.31***	-.25***	-.04	-.07	-.05	.02	-.04	.11*	.04	.01	.02	.27***	.28***	.50***	.23***	.29***	.45***	.45***	.50***	-
Mean	4.03	3.81	3.80	4.20	3.98	4.02	3.85	3.74	3.80	4.51	4.27	4.32	2.91	3.06	3.05	2.29	2.52	2.55	3.07	3.15	3.16
S.D.	.55	.66	.73	.54	.66	.70	.59	.66	.73	.47	.60	.68	.85	.95	.98	.74	.82	.86	.82	.84	.86

Note. $^{***} = p < .001$, $^{**}p < .01$, $^{*}p < .05$. EXP1 = Expectancy Time 1; INT2 = Interest Value Time 2, ATT3 = Attainment Value Time 3, UTL1 = Utility Value Time 1, OPP2 = Opportunity Cost Time 2, EFF3 = Effort Cost Time 3, PSY1 = Psychological Cost Time 1. All items measured on a 5-point Likert scale.

Table 2.
Correlations and Descriptive Statistics for Predictor and Outcome Variables

	ACT^M	Gender	URM	1st Gen	Timing	Major	E_GPA
ESE1	-.04	$-.09^{*}$	$.13^{**}$	$.09^{*}$	.02	.05	-.05
ESE2	.06	-.02	.06	.07	-.06	$.17^{***}$	.01
ESE3	$.19^{***}$	-.10	.04	-.03	.04	$.28^{***}$	$.32^{***}$
INT1	-.02	$-.10^{**}$	$.19^{**}$	$.10^{**}$	-.04	.05	$-.10^{**}$
INT2	.03	-.01	.03	$.10^{*}$	.04	$.23^{***}$	.003
INT3	.06	-.06	.09	.01	.03	$.37^{***}$	$.15^{**}$
ATT1	.07	$-.12^{**}$	.05	.06	-.06	$.08^{*}$	-.07
ATT2	.04	.01	.04	.05	-.01	$.29^{***}$	.002
ATT3	$.11^{*}$	-.03	-.02	-.08	.07	$.43^{***}$	$.19^{***}$
UTL1	.02	-.003	.03	.02	.04	.06	-.06
UTL2	.09	.07	-.06	-.02	$.18^{***}$	$.27^{***}$	.06
UTL3	.08	-.06	.03	-.08	$.12^{*}$	$.39^{***}$	$.13^{**}$
OPP1	-.05	.04	-.01	.04	-.04	.07	.004
OPP2	-.10	-.04	-.07	.02	-.03	-.03	.08
OPP3	-.05	.02	.01	.04	$-.13^{**}$	-.02	-.02
EFF1	-.02	-.04	$-.10^{**}$	-.01	$-.16^{***}$	-.07	-.05
EFF2	$-.10^{*}$	-.02	-.03	.02	$-.12^{**}$	$-.14^{**}$	-.09
EFF3	-.05	-.01	-.01	.03	$-.20^{***}$	$-.19^{***}$	$-.24^{***}$
PSY1	$-.13^{**}$	$.22^{***}$	-.06	.02	$-.09^{*}$	.01	-.05
PSY2	$-.15^{**}$	$.11^{*}$	-.03	.02	-.004	.002	-.08
PSY3	$-.10^{*}$	$.17^{**}$	-.002	.01	-.05	.06	$-.19^{***}$
ACT^M	-						
Gender	$-.12^{**}$	-					
URM	$-.43^{***}$	.07	-				
1st Gen	$-.32^{***}$	-.01	$.23^{***}$	-			
Timing	$.40^{***}$	-.05	$-.16^{***}$	$-.15^{***}$	-		
Major	$.21^{***}$	.01	$-.08^{*}$	$-.10^{**}$	.05	-	
E_GPA	$.35^{***}$	.04	$-.24^{***}$	$-.16^{***}$	$.21^{***}$	$.12^{**}$	-
Mean	28.45	.26	.12	.19	.65	.75	2.99
S.D.	4.18	.44	.32	.39	.48	.43	.92

Note. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$. ACT^M = math subsection score for the ACT, max. score 36; URM = underrepresented minority; 1st Gen = first-generation college student; E_GPA = GPA in 4th semester engineering courses, 4.0 scale; Major = engineering major status (1 = *engineering major*, 0 = *not an engineering major*); Timing = Intro course taken in first semester (1 = yes, 0 = no).

Table 3.
Fit Statistics for Longitudinal Confirmatory Factor Analysis of Expectancy, Task Values, and Costs

Model	χ^2	*df*	CFI	ΔCFI	RMSEA
Expectancy					
Configural	251.57***	87	.955	–	.049
Weak	259.30***	95	.955	.000	.047
Strong	272.75***	103	.954	-.001	.046
Strict	**301.77*****	**113**	**.949**	**-.005**	**.046**
Interest Value					
Configural	249.50***	87	.968	–	.049
Weak	261.24***	95	.967	-.001	.047
Strong	297.04***	103	.965	-.002	.047
Strict	**301.54*****	**114**	**.963**	**-.002**	**.046**
Attainment Value					
Configural	186.97***	51	.943	–	.058
Weak	216.76***	57	.933	-.010	.060
Strong	230.66***	63	.930	-.003	.058
Strict	**242.83*****	**71**	**.928**	**-.002**	**.055**
Utility Value					
Configural	116.05***	51	.978	–	.040
Weak	128.21***	57	.976	-.002	.040
Strong	160.79***	63	.966	-.010	.044
Strict	**191.89*****	**71**	**.959**	**-.007**	**.046**
Opportunity Cost					
Configural	66.94***	24	.981	–	.048
Weak	76.16***	28	.978	-.003	.047
Strong	78.75***	32	.979	.001	.043
Strict	**90.92*****	**38**	**.976**	**-.003**	**.042**
Effort Cost					
Configural	159.39***	51	.946	–	.052
Weak	164.55***	57	.947	.001	.049
Strong	**176.69*****	**63**	**.943**	**-.004**	**.048**
Strict	211.58***	71	.930	-.013	.050
Psychological Cost					
Configural	354.74***	87	.919	–	.063
Weak	366.16***	95	.918	-.001	.060
Strong Partial	402.28***	102	.911	-.007	.061
Strict Partial	**406.78*****	**112**	**.911**	**.000**	**.058**

Note. Bolded lines indicate the selected invariance models used for subsequent latent growth models. Partial invariance for the psychological cost model involved allowing the intercept of one psychological cost item to estimate freely at T1. All other parameters were fixed according to time invariance constraints. $^{***}p < .001$.

Table 4.
Fit Statistics for Unconditional Latent Growth Models

Model	χ^2	*df*	RMSEA	CFI	ΔCFI
Expectancy					
Intercept-Only	434.52^{***}	119	.058	.914	-
Linear	315.12^{***}	116	.047	.946	.032
Interest Value					
Intercept-Only	446.83^{***}	119	.059	.935	-
Linear	339.98^{***}	116	.049	.956	.021
Attainment Value					
Intercept-Only	301.83^{***}	77	.061	.906	-
Linear	253.79^{***}	74	.055	.925	.019
Utility Value					
Intercept-Only	370.14^{***}	77	.069	.899	-
Linear	230.90^{***}	75	.051	.947	.048
Opportunity Cost					
Intercept-Only	122.66^{***}	44	.048	.964	-
Linear	96.86^{***}	41	.042	.975	.011
Effort Cost					
Intercept-Only	272.53^{***}	69	.061	.899	-
Linear	188.96^{***}	66	.049	.939	.040
Psychological Cost					
Intercept-Only	423.88^{***}	118	.057	.907	-
Linear	415.08^{***}	115	.058	.909	.002

Note. The linear growth model for utility value initially resulted in a non-positive definite covariance matrix, but the issue was resolved by fixing the small and non-significant covariance between intercept and slope to zero. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$

Table 5.
Unstandardized Parameters for Unconditional Latent Growth Models

	Intercept Mean		Intercept Variance		Slope Mean		Slope Variance		Intercept & Slope Cov.	
Expectancy	3.93^{***}	(.02)	0.10^{***}	(.02)	-0.14^{***}	(.02)	0.04^{*}	(.02)	0.03^{*}	(.01)
Interest	4.13^{***}	(.02)	0.12^{***}	(.02)	-0.12^{***}	(.02)	0.04^{**}	(.01)	0.03	(.01)
Attainment	3.67^{***}	(.03)	0.21^{***}	(.03)	-0.05^{*}	(.02)	0.08^{***}	(.02)	-0.01	(.02)
Utility	4.53^{***}	(.02)	0.06^{***}	(.01)	-0.13^{***}	(.02)	0.05^{***}	(.01)	0.00	-
Opp. Cost	2.87^{***}	(.03)	0.31^{***}	(.05)	0.09^{***}	(.02)	0.02	(.03)	0.05	(.03)
Effort	2.27^{***}	(.03)	0.27^{***}	(.04)	0.18^{***}	(.02)	0.05^{*}	(.02)	0.02	(.03)
Psych. Cost	2.79^{***}	(.03)	0.30^{***}	(.04)	0.05^{*}	(.02)	0.02	(.02)	-0.01	(.02)

Note. Standard errors are displayed in parentheses. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

Table 6.
Fit Statistics for Conditional Latent Growth Models

Model	χ^2	*df*	RMSEA	CFI
Expectancy	370.999***	226	0.03	0.94
Interest Value	442.069***	226	0.04	0.93
Attainment Value	358.001***	163	0.04	0.89
Utility Value	321.141***	163	0.04	0.93
Effort Cost	339.690***	155	0.04	0.86

***$p < .001$.

Table 7.

Parameters for Predictors of Conditional Latent Growth Models

	Intercept		Slope	
Model and Predictors	b	β	b	β
Expectancy				
Math ACT	0.03	0.07	0.08***	0.35***
Gender	-0.04	-0.05	0.03	0.06
URM	0.25**	0.21**	0.004	0.005
FirstGen	0.16**	0.17*	-0.05	-0.09
Course Timing	-	-	0.04	0.09
Interest Value				
Math ACT	0.01	0.02	0.05**	0.24***
Gender	-0.07	-0.08	0.03	0.07
URM	0.21**	0.17**	0.02	0.03
FirstGen	0.17**	0.18*	-0.03	-0.06
Course Timing	-	-	0.05	0.12
Attainment Value				
Math ACT	0.03	0.08	0.01**	0.22***
Gender	-0.05	-0.05	0.05†	0.11
URM	0.18*	0.12*	-0.02	-0.03
FirstGen	0.13*	0.11	-0.07*	-0.13
Course Timing	-	-	0.06*	0.14*
Utility Value				
Math ACT	-0.02	-0.09	0.04**	0.19**
Gender	-0.02	-0.05	0.02	0.05
URM	0.07	0.10	-0.001	-0.002
FirstGen	0.02	0.04	-0.03	-0.07
Course Timing	-	-	0.09***	0.26***
Effort Cost				
Math ACT	0.02	0.03	-0.06**	-0.24***
Gender	-0.01	-0.01	-0.03	-0.04
URM	-0.30**	-0.15**	0.08	0.09
FirstGen	-0.04	-0.02	0.03	0.04
Course Timing	-	-	-0.18***	-0.36***

Note: *$p < .05$, **$p < .01$, ***$p < .001$

Table 8.

Parameters for Outcomes of Conditional Latent Growth Models

	Retention			GPA	
Model and Predictors	b	β	O.R. (β)	b	β
Expectancy					
Intercept	0.27	0.09	1.09	-0.71	-0.28*
Slope	2.04***	0.42***	1.52	3.22***	0.77***
Interest Value					
Intercept	0.09	0.03	1.03	-0.86**	-0.34**
Slope	3.16***	0.60***	1.82	2.72***	0.60***
Attainment Value					
Intercept	0.62**	0.26**	1.30	-0.35	-0.17
Slope	3.14***	0.62***	1.86	2.44***	0.56***
Utility Value					
Intercept	-0.18	-0.03	0.97	-2.42*	-0.55**
Slope	3.62***	0.62***	1.86	3.56***	0.70***
Effort Cost					
Intercept	-0.30*	-0.16	0.85	0.02	0.01
Slope	-1.54***	-0.37***	0.69	-2.10***	-0.58***

Note: O.R. = odds ratio; **p* < .05, ***p* < .01, ****p* < .001

Table 9.
Variance in Retention and GPA Explained by Each Model with Pairwise Statistical Comparisons

				Z test comparisons			
Retention	r^2	*SE*	*r*	*vs. Interest*	*vs. Attainment*	*vs. Utility*	*vs. Effort*
Expectancy	.202**	0.06	0.45[c]	-3.89***	-6.30***	-3.62***	1.08
Interest	.375***	0.09	0.61[b]		-2.44*	0.27	4.97***
Attainment	.472***	0.09	0.69[a]			2.71**	7.37***
Utility	.360***	0.06	0.60[b]				4.70***
Effort	.157**	0.05	0.40[cd]				
GPA							
Expectancy	.565***	0.14	0.75[a]	4.72***	5.49***	4.72***	5.49***
Interest	.377***	0.11	0.61[b]		0.80	0.00	0.80
Attainment	.331***	0.09	0.58[bc]			-0.80	0.00
Utility	.378**	0.11	0.61[b]				0.80
Effort	.331***	0.08	0.58[bc]				

*$p < .05$, **$p < .01$, ***$p < .001$. Non-common superscripts indicate significant differences as indicated by Fisher *r*-to-*Z* comparisons.

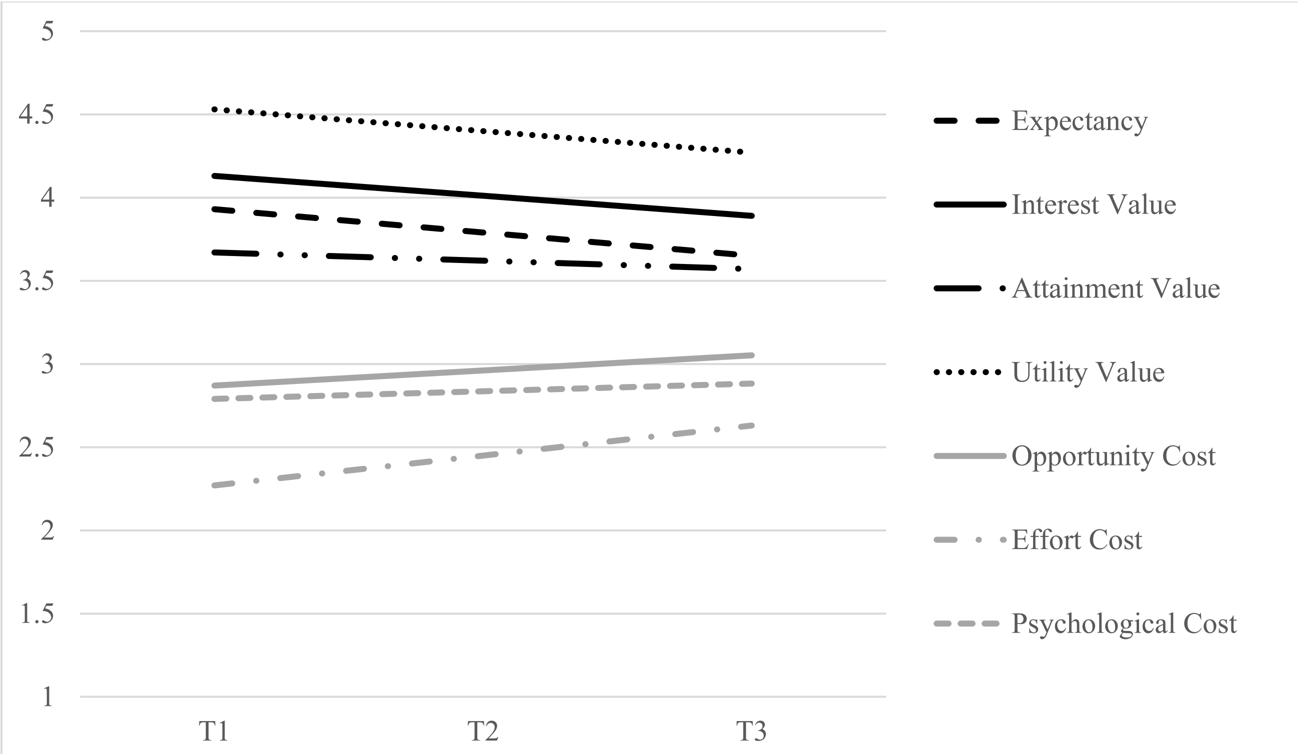

Figure 1. Model-implied trajectories for unconditional models of seven motivation constructs.

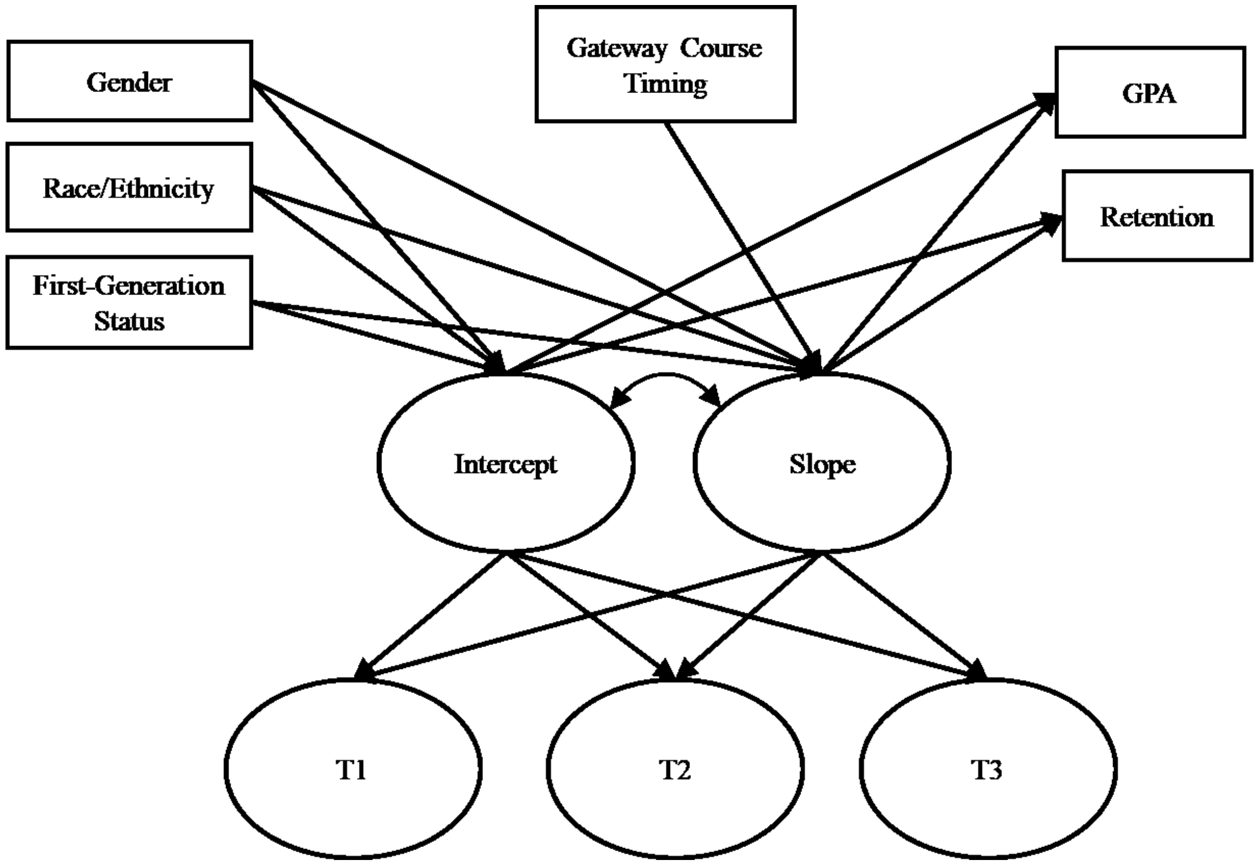

Figure 2. Second-order linear growth model with predictor and outcome, modeled separately for expectancy, interest value, attainment value, utility value, opportunity cost, effort cost, and psychological cost. Not pictured but included in the model were Math ACT scores as a control variable (predicting intercept and slope), and covariances between Math ACT scores and each of the demographic variables.

Appendix

Engineering Academic Perceived Competence (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.
2. I will be able to master the content in even the most challenging engineering course if I try.
3. I will be able to do a good job on almost all my engineering coursework if I do not give up.
4. I'm confident that I can learn the content taught in my engineering-related courses.
5. I'm certain I can earn a good grade in my engineering-related courses.

Interest Value (adapted from Conley 2012)

1. I enjoy the subject of engineering.
2. I enjoy doing engineering.
3. Engineering is exciting to me.
4. I am fascinated by engineering.
5. I like engineering.

Attainment Value (adapted from Conley, 2012 and Pugh et al., 2009)

1. Being someone who is good at engineering is important to me.
2. Being good in engineering is an important part of who I am.
3. Being involved in engineering is a key part of who I am.
4. I consider myself an engineering person.

Utility Value (adapted from Conley, 2012)

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

Opportunity Cost (adapted from Perez et al., 2014)

1. I'm concerned that I have to give up a lot to do well in engineering.
2. I'm concerned that success in engineering requires that I give up other activities I enjoy.

3. I’m concerned about losing track of valuable relationships because of the work required for engineering.
4. I would rather leave more time for fun than for something as intense as engineering (*dropped*).

Effort Cost (adapted from Perez et al., 2014)

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.
2. Studying engineering will require more effort than I’m willing to put in.
3. For me, studying engineering may not be worth the effort.
4. I am not sure if I’ve got the energy to do well in engineering.

Psychological Cost (adapted from Perez et al., 2014)

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