Engineering PhD Returners and Direct-Pathway Students: Comparing Expectancy, Value, and Cost

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Abstract

Background Professionals who pursue a doctorate after significant post-baccalaureate work experience, a group we refer to as returners, represent an important but understudied group of engineering doctoral students. Returners are well situated to leverage their applied work experiences in their advanced engineering training.

Purpose/Hypothesis We drew on results from the Graduate Student Experiences and Motivations Survey to explore the dimensionality of our scales measuring value and cost constructs. We used these scales, as well as measures of student expectancy of success, to compare returners with direct-pathway students.

Design/Method We surveyed 179 returners and 297 direct-pathway domestic engineering doctoral students. We first conducted Exploratory Factor Analysis on our cost and value measures. We then used both Ordinary Least Squares and Ordinal Regression Model analyses to assess the relationships of various student characteristics and experiences (including returner status) with student expectancy of success and the emergent cost and values factors associated with doctoral study in engineering.

Results Factor analysis revealed three categories of values (interest, attainment, and career utility) that were largely consistent with those in Eccles' expectancy-value framework. A similar analysis identified three categories of costs (balance, financial, and academic) associated with pursuing a PhD. Returners felt significantly less confident in their ability to complete their degrees prior to enrolling and perceived higher levels of all cost types than direct-pathway students.

Conclusions Given the differences between returning and direct-pathway students, it is important to consider how universities might best recruit and retain returners. Tracking returner status could be critical in better supporting these students.

Keywords returning students; expectancy-value theory; motivation; graduate education

Introduction

To address calls (e.g., National Academy of Engineering, 2004; National Academy of Sciences, National Academy of Engineering, & Institute of Medicine, 2007) to better support the development of highly skilled engineers, including those with doctoral degrees, it is critical to examine existing pathways and to create new ones through engineering doctoral programs

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(Baker, Tancred, & Whitesides, 2002; National Science Board, 2012). Facilitating multiple pathways through doctoral engineering education can help increase overall enrollment and, equally important, add to the diversity of experiences and perspectives represented in engineering programs. Practicing engineers who return to graduate school to earn their doctoral degrees, a group we refer to as returners, represent one pathway through advanced engineering training programs that has been relatively unexplored in the literature to date.

These returning students with extensive work experience may contribute to the diversity of perspectives and problem-solving approaches needed in engineering to address the complex problems of our global economy; they have the unique set of technical skills engineers are called on to use, and the vision needed to identify important problems and develop innovative solutions in multiple contexts. While a sizeable percentage (14.4%) of recent engineering doctoral graduates pursue careers in academe, the majority of these students' first career is in industry or business (72.1%), with others pursuing government (9.7%), nonprofit (3.1%), or other (0.6%) work (National Science Foundation, National Center for Science and Engineering Statistics, 2015a). The range of postdoctoral employment sectors beyond academia and the diversity of careers in these sectors suggest that engineering programs would benefit from students with a variety of past work experiences and associated skills. Returning students contribute to this diversity of skills and interests and are likely to have extensive experience in various engineering contexts that they can apply to work in a number of employment sectors upon graduation.

Additionally, returning students can integrate their rich prior experiences with the advanced engineering training of their doctoral programs (Peters & Daly, 2012), finding connections between the two contexts and laying the foundation for innovation (Finke, Ward, & Smith, 1996). Returners are also situated to apply their PhD research more immediately and directly because they can tie into their previous experiences and networks as engineering practitioners (Peters & Daly, 2011, 2012). Furthermore, returners are often more goal-oriented, motivated, and mature and generally have a high work ethic and strong teamwork skills (Hofinger & Feldmann, 2001; MacFadgen, 2007; Prusak, 1999). While returners could be positioned to make unique contributions through their work while both at the university and upon completing a PhD, they likely face particular challenges and value distinct elements of earning a PhD that engineering doctoral programs are currently not fully addressing in their efforts to recruit, retain, and support graduate students.

To date, little research has attended to the experiences and contributions of returners pursuing advanced engineering training (Peters & Daly, 2013; Strutz, Cawthorne, Ferguson, Carnes, & Ohland, 2011). Our work focuses on characterizing the experiences of these returning students in engineering doctoral programs. For this study, we define returners as students who have a total gap of 5 years or more not enrolled full-time in school between completing their undergraduate degree and beginning their doctorate. Our working definition of returners here is consistent with the one used in our team's earlier studies (e.g., Mosyjowski, Daly, Peters, & Skerlos, 2013; Peters & Daly, 2013) and reflects research that suggests work identities develop over time, likely beyond one or two years of post-baccalaureate study (Ibarra, 1999; Schein, 1978). We compare returners to direct-pathway students, who begin a PhD program shortly after completing an undergraduate degree (less than 5 years for the purposes of our study). In this study, informed by Eccles' expectancy-value framework for achievement-related choices, we explore student expectancy of success in their doctoral programs and different types of values and costs associated with pursuing a PhD in engineering. Our findings contribute to an understanding of what shapes returners' decisions to pursue and persist in doctoral study in engineering and can ultimately be used to inform efforts to support these students' success.

Background

In engineering and in several other STEM fields, it is the norm for students who pursue PhDs to do so shortly after completing their undergraduate work (Schilling, 2008). Graduation age data show that the average age of engineering doctoral recipients upon completion of their degree is 30, which, accounting for the length of PhD programs, suggests many students begin a PhD fewer than five years after completing their undergraduate work. The average age of PhD completion in engineering is comparable to graduation age data from other STEM areas such as physical and life sciences (29.9 and 31, respectively) but is in contrast to other areas of study such as education (38.3), humanities (34.2), and other non-science and engineering fields (35.1), where it is more common for students to spend time working before pursuing a PhD (National Science Foundation & National Center for Science and Engineering Statistics, 2014). While one key factor contributing to differences in graduation age data between fields is likely the proportion of returning students, other key factors in these differences could be variation in average time to degree and the proportion of students completing their degree part-time while working. Because returner status is not a tracked demographic characteristic, determining students' paths through doctoral programs is a challenge.

A number of studies have focused on the experiences of groups of students typically underrepresented within engineering that may shape their decisions to enroll and persist in engineering programs (e.g., Chubin, May, & Babco, 2005; Crawley, Malmqvist, Ostlund, & Brodeur, 2007). However, few studies aiming to increase the number of engineers with advanced training have examined returning students. We do not assume returners' experiences mirror those of students whose experiences have been shaped by continual systemic discrimination within and beyond engineering; however, work is needed to determine if, given their "nontraditional" path to PhD programs, returners face challenges of their own in engineering education relative to their direct-pathway peers. Peters and Daly (2013) documented various types of struggles returning engineering students face, including those related to financial, balance, intellectual, and cultural and environmental costs. For example, graduate returners reported changes in their financial security, having less time for family or personal interests, having difficulty finding peers to work and study with, and struggling to adapt to the university environment as a student.

Other work that informs the struggles engineering returners face comes from literature on graduate and undergraduate returners across a variety of disciplines, research which cites a number of challenges associated with pursuing additional education. Returners may have difficulty in the admissions process for graduate degree programs, especially when the Graduate Record Examination (GRE) is required as scores older than five years are typically not accepted. If the returner takes the GRE again, much of the information on the test that a student right out of college would have recently learned is unlikely to be as easily recalled by returning students (Schilling, 2008). As a consequence, such measures may not accurately predict their success; for example, Purdy and Washburn (2005) found that the GRE underestimates academic success for women over 24. Once admitted, returners may face other challenges including having less recent practice with advanced mathematics coursework core to graduate engineering curriculum (Prusak, 1999), having a different preferred work style than their direct-pathway peers (Schilling, 2008), and being more likely than their younger peers to have family responsibilities such as children or aging parents, making it more difficult for them to balance school and personal responsibilities (Gardner, 2008; Nettles & Millet, 2006). As a result, returners may not feel they fit in with their peers and could perceive their graduate programs as unwelcoming (Gardner, 2008; Schilling, 2008). While these findings, drawn from literature describing both undergraduate and graduate students in a variety of disciplines, serve as a useful starting point, the particular culture and demographic composition of engineering doctoral programs necessitates a discipline-specific examination of the experiences of returning students within engineering.

Despite the challenges associated with the decision to pursue a PhD in engineering, students from a variety of backgrounds still make that decision because of the value they associate with earning the degree, such as advancing in a career field, increasing their earning potential, gaining the credentials necessary to secure a faculty position, desiring more knowledge within a field, wanting to help others with their work, as a means of making a career change, or even perceiving few other options (Anderson & Swazey, 1998; Kubatkin & Christie, 2006; Sheppard, et al., 2010). However, the particular values or motivations for pursuing an engineering PhD have been shown to vary based on student characteristics. For example, while both women and men report consideration of similar elements in their decisions to pursue graduate study in engineering, women rate intrinsic factors as more important in their decision, while men rate factors related to career attainment more highly (Battle & Wigfield, 2003). However, it is likely that intrinsic motivation, which Battle and Wigfield suggest is more salient for women in this context, may be more easily undermined by negative feedback (Deci, Koestner, & Ryan, 1999; Vallerand & Reid, 1988).

While studies have provided insights into the experiences and motivations of various groups of doctoral students, few have specifically addressed the motivations of returners who choose to pursue PhDs in engineering. Peters and Daly (2012, 2013) found that engineering graduate returners cited the perceived utility of the degree as a key reason for pursuing a doctorate. Additional commonly cited motivations for returning included transitioning into an academic career, changing specialty areas within their career in industry, and advancing further in their current career path. Though factors related to career success were most common, Peters and Daly (2013) also identified several other motivations returners cited in their decision to pursue a PhD, including their interest in or passion for the subject material and a sense that earning an advanced engineering degree was fundamentally aligned with their self-concept. Ciston, Carnasciali, Zelenak, and Hollis' (2012) work on undergraduate returning students in engineering documented several motivations for their pursuits to earn an engineering degree, including the ability to financially support themselves and their families, a sense of personal challenge, and an intrinsic interest in engineering. However, it is unclear how the common motivations to return for an undergraduate degree translate to the common motivations to return for an engineering PhD.

Theoretical Framework

To explore returning and direct-pathway students' decisions to enroll and persist in engineering doctoral education, we developed the Graduate Student Experiences and Motivations Survey (GSEMS). The GSEMS instrument and our subsequent data analyses drew on Eccles' expectancy-value theory as a framework (Mosyjowski et al., 2013). This theory posits that individuals' achievement related choices are motivated by expectations of success (or beliefs about their competence) given a particular task and beliefs about value of that task

(Eccles, 2005, 2009; Wigfield & Eccles, 2000). Individuals' competence beliefs and the value they associate with a particular choice are informed by their past experiences, personal identity beliefs (including those related to gender or race/ethnicity), the societal/cultural context, and their interactions with these cultural norms or expectations (Eccles, 2009; Wigfield & Eccles, 2000).

Eccles' (1983) expectancy-value model has its roots in an earlier expectancy-value model developed by Atkinson (1957) and was first conceptualized in a study seeking to explain differing rates of enrollment in science and engineering undergraduate degree programs by gender (Eccles 1983; Eccles 2014). Eccles' model expanded the traditional model, which focused primarily on individual motivation and agency, to provide a more detailed conception of values and to account for the structural influences and gender-role socialization that partially shape individuals' expectation beliefs and values. Eccles and colleagues further refined this expectancy-value model of achievement-related choices, ultimately identifying the four elements of subjective task value, interest-enjoyment value, attainment-achievement value, utility value, and relative cost (Eccles & Wigfield, 1995; Eccles, 2005). In addition, this model includes perspectives from both psychological theories that allow for the role of personal agency in selecting a particular path as well as socio-cultural models which emphasize the role of structural forces that shape and constrain the opportunities and possible paths available to individuals (Eccles, 2014).

In Eccles' model, the construct of expectancy of success is conceptually related to self-efficacy, which is a key component of most cognitive theories of motivation (Eccles & Wigfield, 1995; Matusovich, Streveler, & Miller, 2010). Self-efficacy, as characterized by Bandura (1977), refers to an individual's assessment of his or her ability to perform a task, often conceptualized within a specific domain. Self-efficacy theories, or the related concept of competency beliefs, have been common frameworks for understanding students' decisions to enroll and persist in engineering (Jones, Paretti, Hein, & Knott, 2010; Matusovich et al., 2010), with studies suggesting that students' competency beliefs and perceptions of task difficulty relate to their interest in and pursuit of training in a STEM field (Lent et al., 2008). While many studies have demonstrated the role of gender in self-efficacy in STEM fields (Marra, Rodgers, Shen, & Bogue, 2009; O'Brien, Martinez-Pons, & Kopala, 1999), competency beliefs alone do not fully account for students' choices to enroll and persist in engineering (Bembenutty, 2008; Eccles, 1983; Godwin, Potvin, Hazari, & Lock, 2016; Matusovich et al., 2010).

By considering both competency beliefs as well as the subjective task value an individual assigns to a particular achievement-related outcome, Eccles' model (2009) allows for a more nuanced understanding of individuals' decisions to pursue and persist in doctoral study. Eccles' model with its four elements of task value—interest-enjoyment value, attainment value, utility value, and relative cost—provides a framework for examining motivation beyond self-efficacy as well as the characteristics and experiences that influence individuals' values and competence beliefs. Interest-enjoyment value, the anticipated enjoyment of engaging in the activity itself, is likely to eventually be incorporated into an individual's self-concept, while attainment value relates to how a particular choice fulfills an individual's personal needs, values, and identity, including personality, goals, schemas based on societal norms, and ideal images of self. Utility value refers to an individual's perception of the advantages of a choice in helping to fulfill a less personally centered goal, such as financial benefit. Finally, relative cost includes an individual's perception of the sacrifices required, including effort, time, and psychological impact. Eccles and colleagues argue that both these values and students' expectancy of success are related to a variety of influences, including cultural norms, past experiences, individual strengths and personality, the way an individual is socialized (through interactions with parents, teachers, peers, etc.), and self-perceptions (Eccles, 2009).

In our team's earlier study, which involved interviews with ten returning graduate students in engineering, we found that the broad categories of values included in Eccles' (2009) expectancy-value model reflected the motivations for returning expressed by participants (Peters & Daly, 2013). The returners in this study also identified a variety of specific types of costs associated with the achievement-related choices of pursuing and persisting in engineering graduate study after significant work experience, which our team categorized into several sub-categories. These cost categories proposed in this earlier work include (a) financial costs, described as challenges or sacrifices related to money, including changes in financial security or tuition costs, (b) balance costs, those challenges related to competing time commitments both internal and external to graduate school, (c) intellectual costs, related to learning the content and academic work associated with engineering doctoral study, and (d) cultural/environmental costs, those challenges associated with adapting to a new climate and managing relationships with new colleagues within graduate school. Given the origin and focus of these cost sub-categories, they are not meant to be a universally applicable extension of Eccles' expectancy-value model, but rather they provide a useful, relevant framework in considering the potential costs of pursuing an engineering PhD in more detail than the broad relative cost category proposed in the expectancy-value model (Wigfield & Eccles, 2000).

Considering cost as its own factor within the expectancy-value model is consistent with an increased attention to the role of cost in achievement-related decision making (Barron & Hulleman, 2015). Flake, Barron, Hulleman, McCoach, & Welsh (2015) pointed to the importance of cost as a separate construct because it is a distinct factor noticed by students in their experiences separate from the various types of values they see in the experience and has been found to directly link to educational outcomes. Thus, they call for more attention to the definition and measurement of cost as part of the expectancy-value framework. A close examination of cost as an element of the expectancy-value framework was also the topic of a symposium at the 2016 American Education Research Association annual conference led by Allan Wigfield, entitled "Extending the Expectancy-Value Model: Definitions and Functions of Cost in Students' Choice, Engagement and Performance." Several presentations in this session advocated for a consideration of cost as a distinct element in the expectancy-value model, or an expectancy-value-cost model (Barron, Hulleman, Flake, Kosovich, Lazowski, 2016; Jiang, Kim, & Bong, 2016).

Expectancy-value theory has been applied widely in engineering and beyond to understand how students make decisions to pursue particular fields of study (Frome, Alfeld, Eccles, & Barber 2006; Matusovich, et al., 2010; Matusovich, Streveler, Loshbaugh, Miller, & Olds, 2008) and how personal identities affect academic decision making (Battle & Wigfield, 2003), for example how gender influences participation in science and engineering fields (Eccles, 2007). In one such study focusing primarily on gender, Eccles (2007) suggested that differing levels of participation in physical science and engineering fields by gender are due not to aptitude nor students' perceptions of their ability to succeed, but to gender differences in the values and costs students place on different career paths. However, other studies have suggested that lower self-efficacy plays a more important role in women's participation in engineering (Marra et al., 2009).

The use of expectancy-value theory in other studies of engineering pathways informed our use of the model in our research. We determined expectancy-value theory was an appropriate framework to inform our exploration of how returner status relates to students' graduate school experiences associated with their motivation to enroll and persist in their academic programs based on 1) the original purpose of expectancy-value theory and its subsequent use as a framework for understanding students' achievement-related decision making, often specifically in STEM fields, 2) its nuanced treatment of student motivation beyond strictly competence beliefs, 3) its allowance for social and cultural influences on student values and decision making, and 4) our team's earlier pilot study that indicated a good theoretical fit (Peters & Daly, 2013). The model guided the development of the survey instrument, data analysis, interpretation of results, and recommendations for practice.

Research Method

Research Questions

The goal of this study was twofold: 1) to develop and initially validate meaningful scales to measure the costs and values associated with engineering PhD students' decisions to pursue a PhD and 2) to use these cost and value scales and questions related to students' expectancy of success in their PhD to understand the perspectives and experiences of returners compared to those of direct-pathway students. We specifically focused on those components of expectancy-value theory that may help explain returning and direct-pathway students' decisions to pursue and persist in engineering PhD programs. More specifically, our study was guided by the following research questions:

> Q1: What are the latent dimensions of the costs and values associated with pursuing an engineering PhD measured by our instrument?
>
> Q2: Do returners' perceptions of expectancies, values, and costs of earning an engineering PhD differ from those of direct-pathway students? If so, how do they differ?

Instrument Development

Data were collected using the Graduate Student Experiences and Motivations Survey (GSEMS), an instrument designed by our team (Mosyjowski et al., 2013). We developed the GSEMS by drawing on findings from an earlier qualitative study (Peters & Daly, 2013) that supported the use of Eccles' expectancy-value theory as an appropriate model for understanding the decision process for returners for pursuing a PhD, as well as literature on returners and engineering graduate students more broadly and the experiences of our diverse team. The GSEMS was developed to allow us to better understand the backgrounds, experiences, and motivations of returning and direct-pathway students. The survey includes questions related to 11 primary areas:

- demographic information (10 questions)
- academic background information (11 questions)
- current academic information (12 questions)
- pre-PhD activities and career (5 questions)
- decision to pursue a PhD (9 questions)
- expectancy of success in the doctoral program (5 questions)
- values of the PhD (2 questions)

- costs of the PhD (3 questions)
- cost reduction strategies (3 questions)
- advising relationship (2 questions), and
- post-PhD plans (4 questions).

The GSEMS instrument included a total of 68 questions, many of them multi-part or composite questions.

The development of the GSEMS instrument was a rigorous process guided by the literature on approaches for establishing the validity of a survey instrument (Creswell & Miller, 2000; Douglas & Purzer, 2015; Schutt, 2006), including grounding the instrument in theory, using qualitative studies to inform the development and refinement of questions, and conducting cognitive interviews and think-aloud protocols to check for interpretation of items and to gauge the extent to which the question aligned with the types of responses we hoped to elicit. The GSEMS instrument stems from our team's earlier study involving interviews with returning students that suggested an expectancy-value model was consistent with how returners talked about their graduate school experiences (Peters & Daly, 2011, 2012, 2013). We then developed a number of questions drawing on these qualitative data as well as expectancy-value theory, literature on returning students, and our team and advisory panel's diverse professional and academic experiences, including one member who was a returner herself, industry professionals, and a former graduate chair who had mentored returning students. This survey development process reflected a number of recommended validity measures, including triangulating information from multiple data sources in the development and refinement of our scales, seeking disconfirming evidence, practicing reflexivity, and debriefing with peers familiar with the research method and topic (Creswell & Miller, 2000). After developing a draft of our survey, we conducted think-aloud cognitive interviews with returning students in other STEM fields to help us assess and refine it (Collins, 2003). Mosyjowski et al. (2013) provide further detail about our survey development process and the early approaches we took to help ensure its validity during the development of the GSEMS instrument. In our current paper, we describe subsequent efforts to assess the validity and reliability of the GSEMS, particularly our measures of the costs and values associated with earning a PhD.

Data Collection

We distributed the GSEMS to both returning and direct-pathway domestic students across the United States in several waves, beginning in October 2012 and ending in February 2013. Given variation in "typical" paths through undergraduate and graduate degree programs across countries (including compulsory military service requirements, varying interpretations of the purpose of a PhD, and visa processes that might influence students' time to degree and choices during and after their degree programs), we chose to focus only on domestic United States citizens and permanent residents. Though international scholars made up nearly 56 percent of U.S. engineering doctoral recipients in 2013 (National Science Foundation, National Center for Science and Engineering Statistics, 2015b), given the size and scope of our study, we anticipated being unable to meaningfully account for students' countries of origin in considering the ways returner status shapes their academic experiences.

We sought to recruit a roughly balanced pool of returning and direct-pathway students to have a sufficient sample of each for the sake of comparison. Because returner status is not a tracked demographic and data on age at graduation suggest that returners are a minority of engineering PhD students, we employed several sampling strategies that allowed us to identify potential returners before sending out invitations to participate in the survey. We emailed the chairs of 84 engineering graduate programs across the country, asking them to distribute an introductory email and link to a screening survey inquiring about undergraduate and master's degree program dates and durations as well as PhD start dates to their domestic PhD students. Of the chairs contacted, 31 agreed to forward our email to their doctoral students. Our sampling of institutions started in the Midwest and was expanded nationally over several waves, focusing on capturing a range of institutions but also on first contacting those colleges of engineering with large doctoral enrollments. We contacted 80% of all institutions that granted more than 20 doctoral degrees in engineering in 2013. While we could not randomly sample from the graduate student population across the nation, and thus cannot claim generalizability, our sample was diverse as the institutions in it represent a broad range of programs nationally that offer engineering PhDs in terms of their size, geography, and selectivity.

In addition to contacting institutions, we also identified individual students using the NSF Graduate Research Fellows database and sent screening surveys to those who had matriculated in engineering doctoral programs up to 3 years prior to our survey date. We also engaged in limited snowball sampling to identify additional returners. At the end of our survey in early waves of distribution, we asked participants if they knew of additional PhD students with significant work experience who might be interested in participating. A total of 14 returners were recruited to participate through referrals by their peers. Because we employed multiple recruitment approaches, we checked student email addresses prior to screening survey distribution to ensure no duplications.

Based on student responses to our screening surveys, we identified returners and direct-pathway students, sending survey invitations to all returners and an approximately equal-sized random sample of direct-pathway students (rounding to the nearest 5 participants). Though surveying all direct-pathway students would have resulted in a larger sample, given our need for a sizable sample of returning students and limited resources for participant compensation, we felt this sampling approach was the most viable strategy. Of the students who completed the screening questionnaire and were sent invitations to the final survey, 546 responded, giving us a response rate after the screening questionnaires of 72 percent. After eliminating international participants (to account for differences in degree paths in other countries) and incomplete responses (any cases in which the participant completed less than 75% of the survey), the survey yielded 476 usable responses. The sample included returning and direct-pathway students attending 61 different universities across 30 states. Approximately 94% of students in our sample attended universities with a Carnegie designation of "Research University/Very High Activity" (RU/VH), compared to approximately 80% of all engineering doctoral students nationally (National Science Foundation, National Center for Science and Engineering Statistics, 2013). Returners accounted for 179 of the 476 total participants. Approximately 35 percent of respondents were female (compared to 22.2 percent of engineering doctoral students nationally), and 14 percent identified as an underrepresented minority (those students who identified as Hispanic/Latino/a, African American or Black, American Indian or Alaska Native, and/or Hawaiian Native or Pacific Islander), compared to 11.9 percent of domestic engineering doctoral students nationally (National Science Foundation, National Center for Science and Engineering Statistics, 2012). Approximately 10 percent of students were pursuing a PhD part-time and 19 percent were employed during their doctoral program. While the majority of students surveyed had a bachelor's degree in an engineering field, a notable 20 percent did not. Although the majority of students without an undergraduate engineering background majored in other STEM fields, several had social science and humanities backgrounds. More detailed descriptive information about our sample organized by returner or direct-pathway status is listed in Table 2. Data from the GSEMS are not publicly available and individual participant identities are anonymous.

Measures

Our outcome variables of interest were those related to student expectancy of success, the values students associate with earning a PhD in engineering, and the perceived costs of pursuing a degree. These three categories of outcome variables are intended to reflect different elements of Eccles' (2005) expectancy-value model, which explains such individual achievement-related choices as the decision to pursue or persist in a particular field of study based on the expectancy of success at the task and the subjective value they assigned to that task, including associated costs. Given literature and findings from our team's earlier qualitative study suggesting returning students face various types of costs associated with returning (Peters & Daly, 2013) as well as recent literature advocating for a closer consideration of the role of cost in the expectancy-value model (Flake et al., 2015), we elected to break down cost in more detail than Eccles' model, exploring it as its own multi-faceted category rather than as a sub-type of subjective task value. Table 1 provides an overview of how the measures developed and utilized in this study map onto an expectancy-value conceptual model. The section below provides additional information about how each measure is defined, with more information provided in the analysis section about the factor analyses we used in this study to explore and validate our cost and values scales.

The GSEMS survey included two questions intended to reflect student expectancy of success as conceptualized in Eccles' expectancy-value framework (2005). These two items, specifically relating to students' expectancy of success prior to and during their PhD, are analyzed as distinct outcome variables in this paper. We asked students to assess on a 5-point Likert scale how confident they were in their ability to successfully complete their PhD prior to enrolling as well as at the time of the survey. The scale for these two items ranged from 1 = Very unconfident to 5 = Very confident. For the purposes of this analysis, all questions

Table 1 Conceptual Model and Associated Outcome Measures

Conceptual model	Measures used in analyses
Expectancy of success	Expectancy of success
	Pre-PhD expectancy of success
	Current expectancy of success
Subjective task value	Values
Interest-enjoyment value	Academic interest value
Attainment value	Attainment value
Utility value	Career utility value
Relative cost	
	Costs
	Financial cost
	Balance cost
	Academic cost

related to expectancy of success, values, and cost rated on a 5-point scale were treated as ordinal data.

The survey includes 23 variables related to the value or benefits students associate with earning a PhD that aligned conceptually with one of the three types of subjective task values identified by Eccles (Eccles, 2005, 2009; Wigfield & Eccles, 2000) in the expectancy-value model: interest, attainment, and utility. The fourth value identified by Eccles, cost, we opted to explore based on the specific types of costs identified in our prior work. Students were asked to indicate "how important each of the following factors are as benefits in earning your PhD" on a 5-point Likert scale where 1 = Not at all important and 5 = Very important. To examine the dimensionality of our scale of the values associated with pursuing a PhD and to evaluate the alignment between our scale and the intended groupings of the value variables, we conducted exploratory factor analysis (explained further in the analyses section) of the value variables. We calculated regression factor scores, which account for the extent to which each latent factor is manifested by each individual's observed responses (DiStefano, Zhu, Mindrila, 2009), on each of our three factors–academic interest, attainment, and career utility. These factors, explained in greater detail in our findings, which are conceptually consistent with Eccles' (2005) types of subjective task values, are specific to our measure of values associated with pursuing a PhD. These factor scores were used as the dependent variables for our value models. Reliability estimates for all models were in an acceptable range (Cronbach's alpha of $\alpha=.78$ to $\alpha=.87$) (Gliem & Gliem, 2003; Tavakol & Dennick, 2011). In the value models, a higher factor score indicates a higher perceived importance of that particular category of the value of pursuing a PhD.

Expanding on Eccles' conceptualization of cost as one element of subjective task value, the GSEMS includes 35 variables related to the costs students perceive related to earning a PhD (Eccles, 2005). These variables were selected to reflect financial, balance, intellectual, and cultural/environmental costs. Participants were asked to rate each of the cost types on a 5-point Likert scale to indicate the degree to which each was a challenge, with 1 = Not at all challenging and 5 = Very challenging. Similar to our treatment of value variables, we also factored the 35 cost variables included in the GSEMS survey. The results of our factor analysis revealed three latent cost variables: financial cost ($\alpha=.74$), balance cost ($\alpha=.88$), and academic cost ($\alpha=.86$), all of which were also found to be reliable measures. We predicted regression factor scores for each of these variables, using these scores as outcome variables in our cost analyses, with higher factor scores indicating higher perceived costs. A complete list of all of our value and cost scale items is included in Appendix A.

Our primary independent variable of interest was returner status, a dichotomous variable where a "1" indicated a student met our criteria of a returner. We defined returners as those students who have a total, though not necessarily continuous, gap of five years or more of not being enrolled full-time in school between completing their first undergraduate degree and beginning their current PhD program. For those students who pursued a Master's degree part-time while working, the years enrolled in a Master's program also counted as gap years. For students enrolled in a Master's program full-time, we subtracted the length of their programs from the total years between completing their undergraduate work and beginning their doctorate to calculate their total gap years. While a five-year gap is not a universal way for categorizing returning student status, it is consistent with the definition of returners used in our earlier work. We selected this five-year criterion because it represents significant time away from a university and sufficient time to become established in a field. Research on professional identity development suggests that these identities develop and evolve over multiple years of work and learning within a field (Ibarra, 1999; Schein, 1978). Students with a five-year gap or more in our preliminary study expressed feeling different from their direct-pathway peers. We used the five-year gap criterion both for survey recruitment and analysis purposes.

The remaining independent variables included in our analysis are listed in Table 2, including the descriptive statistics and the specific models in which each variable was used. Certain variables characterizing student demographic information and academic background were included in all models. Other variables were model-specific, as informed by theory and previous studies. In some cases, variables were included or excluded due to the timing of a particular experience. For example, students' assessment of their family's supportiveness for their decision to pursue a PhD is included in the model for pre-PhD expectancy of success but not for measures of students' current expectancy of success or experienced costs, as family support may vary prior to and during the PhD. Similarly, variables related to students' experiences during their PhD were not included in the model for their pre-PhD expectancy of success. In the current expectancy of success model, we chose to use academic cost instead of grade point average because academic cost is more comprehensive and our analyses demonstrated the two were strongly related in our data. Further, there was insufficient distribution of grade point averages to run diagnostics on our expectancy model if they were included, and we found their inclusion did not affect our findings. The value models included students' possible career plans as what they hope to do with a PhD may be related to the value they assign to the degree. The cost models included variables informed by literature on potential challenges faced by returning PhD students, including workload, funding, academic background/preparedness, and academic performance (Gardner, 2008; Nettles & Millet, 2006; Prusak, 1999; Schilling, 2008).

Finally, given the number and range of institutions attended by the study participants, our models also controlled for research spending per full-time equivalent enrollment as a proxy for institutional type (with the exception of the pre-PhD expectancy model since it refers to students' expectations prior to their degree). We matched spending data from the Integrated Postsecondary Education Data System (IPEDS) to each student's institution and used spending as a continuous independent variable in our regression models.

Analyses

Factor Analysis To address our first research question regarding the dimensionality of the scales examining the costs and values students associate with earning a PhD and to generate meaningful outcome measures of students' perceptions of costs and values, we conducted exploratory factor analyses on both our cost and value measures. Because they were measured on different scales and recent literature supports cost and value as distinct constructs, we conducted these analyses separately. We used a principal axis factoring (PF) approach for both measures, which focuses on the common variation between the variables of interest (Costello & Osborne, 2009; McDonald, 2014; Tabachnick, Fidell, & Osterlind, 2001). This approach is consistent with the objective of our analyses to identify meaningful latent variables representing core dimensions of values that could then be used as dependent variables in a regression model.

The exploratory factor analysis for our value scale revealed three value factors with Kaiser Eigenvalues greater than one, a common threshold for identifying how many factors to retain (Costello & Osborne, 2009; McDonald, 2014; Tabachnick et al., 2001). Based on this criterion and an examination of a scree plot that indicated a flattening around 4 factors, we

Table 2 Independent Variable Descriptive Statistics

	Returners		Direct-pathway	
Variable	Obvs.	Proportion or mean (Standard deviation)	Obvs.	Proportion or mean (Standard deviation)
Demographic variables				
Returner status	179	–	297	–
Age	177	37.2 (8.40)	297	26.6 (3.00)
Female	179	0.33	296	0.36
Underrepresented minority	179	0.16	297	0.13
Part-time student	179	0.20	297	0.04
Employed during PhD	179	0.31	297	0.12
Married	179	0.64	297	0.37
Divorced	179	0.06	297	0.01
Single	179	0.30	297	0.62
Has children	178	0.41	297	0.10
Bachelor's in engineering	179	0.74	296	0.84
Characterizing PhD experience (Included in cost models)				
Institutional research spending per FTE (in 10,000s)	177	1.48 (1.42)	296	1.70 (1.65)
Hours worked per weekend	179	8.4 (5.30)	294	7.2 (5.30)
At least partially self-funded PhD	179	0.25	297	0.09
Completed qualifying exam	179	0.62	297	0.64
PhD grade point average	173	–	279	–
2.34–2.66 (C + to B-)	1	0.01	1	0.004
2.67–3.00 (B- to B)	0	0.00	3	0.01
3.01–3.33 (B to B+)	10	0.06	15	0.05
3.34–3.66 (B + to A-)	25	0.14	74	0.27
3.67–4.00 (A- to A)	137	0.79	186	0.67
*Possible career plans (Included in value models)***				
Academic career	179	0.74	297	0.64
Self-employed	179	0.45	297	0.40
Return to previous job	179	0.30	297	0.10
Work in industry	179	0.53	297	0.66
Work in government	179	0.27	297	0.42
Not work in engineering	179	0.08	297	0.12
Undecided	179	0.08	297	0.11
Challenges and support (Included in expectancy of success models)				
Family supportiveness of pursuing PhD*	152	4.44 (0.86)	291	4.63 (0.75)
Academic cost (factor score)	148	0.11 (1.01)	258	−0.07 (0.89)
Advisor helpfulness index	177	3.72	293	3.62

Note: Means for the dependent variables not included because factor scores all have a mean of 0; see Tables 1 and 2 for loadings.

*Family support rated on a 5-point Likert scale where 1=Very Resistant and 5=Very Supportive

**Participants could select more than one potential career plan, coded in models as dichotomous variables independent from one another.

retained three factors, dropping two variables (gaining teaching experience and changing professional environment) from our analysis that had factor loadings less than 0.33 after rotation. We used a promax oblique rotation method (Hendrickson & White, 1964), which allows for factors to be correlated and is grounded in an assumption that our factors are not necessarily statistically independent from one another. Promax rotation represents a more conservative, rigorous approach when one is not certain of statistically independent factors. We generated factor scores for the three value factors for use in our regression models.

An exploratory factor analysis of the cost variables also revealed three factors with Eigenvalues greater than 1. We retained all three based on this criterion and an examination of a scree plot. Consistent with our rationale for the value scale, we applied a promax oblique rotation that allowed for our cost factors to be correlated with one another. After rotation, there were five cost variables with factor loadings below 0.33 for all factors (lower professional status, time away from work, maturity of peers, advisor treatment, and class participation expectations). We opted to drop these variables from our model and re-run our analysis to ensure a three-factor cost model was still the best solution both conceptually and mathematically. We predicted regression factor scores for three cost factors (academic, balance, and financial cost), which we used as the dependent variables in our cost regression analyses. All factor scores used in our models are normalized to a mean of 0.

Expectancy of Success To explore how returner status and other variables were associated with students' expectancy of success in their PhD, we estimated two ordinal logistic regression models (ORM): the first modeled students' pre-PhD confidence in their ability to complete their degrees, and the second modeled their current confidence in their ability to successfully complete their degrees. The model of students' reported expectancy of success before beginning their PhD program included core demographic variables as well as their academic background (represented as *Demo&Acad* in the model below) and their perceptions of their family support of their decision to pursue a PhD (*Family Support*) as independent variables. The model of students' current reported expectancy of success included similar demographic and academic characteristics including institutional research spending (*Demo&Acad*) as well as students' perceptions of their academic costs and support (*AcademicCost&AdvisorSuppt*), specifically the academic cost factor score and an index (on a scale of 1–5) of perceptions of advisor helpfulness (see Appendix A for items in the index). These variables allowed us to examine the role of academic experiences and support in students' expectations of success. The models, represented symbolically, are depicted below:

$$PrePhDExpectancy = \alpha + \beta_1 Demo\&Acad + \beta_2 FamilySupport + \epsilon$$

$$CurrentExpectancy = \alpha + \beta_1 Demo\&Acad + \beta_2 AcademicCost\&AdvisorSuppt + \epsilon$$

Both models met the core assumption of ORM of parallel regressions, suggesting the relationship between all adjacent pairs was acceptably similar for the purposes of interpretation.

Costs and Values Next, to assess the ways returner status was associated with the costs and values of pursuing a PhD in engineering, we estimated several ordinary least squares regression models to examine variables associated with different perspectives related to the costs and the values of a PhD. We used the value and cost factor scores to explore how students' demographic traits and academic and work experiences were associated with the perceived importance of each of the value factors and the extent to which the cost factors were a challenge in their pursuit of a PhD. Many of these demographic and academic experiences (*Demo&Acad*), such as age, gender, race, having partners or families, work commitments, and academic performance, have been identified as influencing student experiences and academic success (Brus, 2006; Gardner, 2008; Nettles & Millet, 2006; Ong, Wright, Espinosa, & Orfield 2011; Peters & Daly, 2013; Sax, 2008; Tonso, 2014). In the regression models for the values, we regressed each category of value factor scores on the core demographic/

academic variables as well as students' plans upon earning their degrees (*PossibleCareerPlans*). Represented symbolically, these models are as follows:

$$AcademicInterest = \alpha + \beta_1 Demo\&Acad + \beta_2 PossibleCareerPlans + \epsilon$$

$$Attainment = \alpha + \beta_1 Demo\&Acad + \beta_2 PossibleCareerPlans + \epsilon$$

$$CareerUtility = \alpha + \beta_1 Demo\&Acad + \beta_2 PossibleCareerPlans + \epsilon$$

Independent variables in the regression models for cost regressed each of the three cost factors on the same demographic and academic variables (*Demo&Acad*) as well as if students had completed their qualifying exams, the average number of hours each weekend spent on academic work (*WeekendHours*), whether students had to at least partially self-fund their degrees (which did not include employer sponsorship or funding) (*SelfFund*), and students' PhD grade point average (*PhDGPA*). These models represented symbolically are:

$$FinancialCost = \alpha + \beta_1 Demo\&Acad + \beta_2 WeekendHours + \beta_3 SelfFund + \beta_4 PhDGPA + \epsilon$$

$$AcademicCost = \alpha + \beta_1 Demo\&Acad + \beta_2 WeekendHours + \beta_3 SelfFund + \beta_4 PhDGPA + \epsilon$$

$$BalanceCost = \alpha + \beta_1 Demo\&Acad + \beta_2 WeekendHours + \beta_3 SelfFund + \beta_4 PhDGPA + \epsilon$$

For both the cost and value models, we ran a series of regression diagnostics to assess model specification and check for potential problems such as multicollinearity of independent variables and heteroskedasticity (unequal variance in the dependent variable across different values of an independent variable) (Belsley, Kuh, & Welsch, 2005; Breush & Pagan, 1979). Calculation of the variance inflation factors for each of the models revealed no evidence of likely multicollinearity. However, our diagnostics (here a Breush-Pagan/ Cook-Weisberg test) indicated likely heteroskedasticity in all six of our regression models, which we addressed by applying robust standard errors to each.

Limitations of the Methods

One limitation of our study was missing data, particularly for the cost outcome measures. There were 70 incomplete responses to our cost measures, limiting the size of our cost factors and subsequent analyses. This issue probably resulted from confusion about the question's compound design, in which participants were first asked if they anticipated a particular challenge and then asked to indicate their experienced level of challenge. Many participants who did not indicate they anticipated a particular challenge did not respond to the second part of the question, which is the focus of the current analysis. We intend to correct for this issue in future versions of the GSEMS instrument. There were also missing data on a much smaller scale for several other items, particularly those asking participants to recall a grade or test performance measure or those that included skip logic for questions that might not be relevant to all students (e.g., family support of pursuing a PhD). These missing data reduced our sample size for our regression analyses. Such missing data are best characterized as missing at random (MAR) as missingness is unlikely to be related to the underlying values of the missing items (Cheema, 2014). We used a multiple imputation approach to assess the influence of these missing data on our findings on our cost variables and re-ran the cost regressions with the imputed data. Multiple imputation is a rigorous method that imitates natural variation in missing data by creating multiple data sets and averaging them into a single dataset (Rubin, 2004). We found our results were not sensitive to missing data as our imputed results did not differ substantially from our original findings, nor did the significance of our findings related to the variables of interest change.

An additional limitation was the inability to account for all variables that might influence student expectancy of success, values, and perceived costs. It is possible that some of the variables that might have influenced these elements of students' PhD experiences would also covary with returner status, our primary independent variable of interest. For example, due to the large number of institutions represented in our survey and our relatively small sample size, we were unable to control for all institutional characteristics (such as selectivity, size, and region) that might influence elements of student experience as well as the likelihood that returners enrolled at that particular institution (though we did include research spending per full-time enrollment equivalent as one way to control for institution type). Additionally, given the numerous subject areas in engineering doctoral degrees, including many dual-focus degrees, we were unable to control for degree field, which is likely another important contextual influence on student PhD experience. In instances where these unmeasured predictor variables are related both to the dependent and independent variable of interest, the effect of the confounding variable is absorbed into the effect of the independent variable, making it difficult to determine the isolated effect of the independent variable (here, returner status) alone.

In addition, given the complexities associated with identifying and surveying a sample of an untracked population (with finite resources), we are unable to make generalizable claims about engineering doctoral students in the United States. Focusing on representation of returners and oversampling this group necessitated tradeoffs in the extent to which we were able capture a representative sample, particularly from racial/ethnic minority students already underrepresented in engineering.

While our comparison of returning and direct-pathway students relies on all elements of Eccles' expectancy value model, our study placed particular emphasis on the development of scales that measured the cost and value elements of this model. The construct of student expectancy of success, which was not explored at the same level of detail in this paper, is measured by two items: one relating to student pre-PhD expectancy of success and one relating to student current expectancy. These broad questions about student expectancy reflect our emphasis on the cost and value measures, limiting our ability to measure more task- and domain-specific expectancy, given the variety in degree stages and fields of study represented by the participants in our study. Similarly, general one- or two-item measures of expectancy of success are not unprecedented in engineering education research (e.g., Giesey, Chen, & Hoshower, 2004; Jones et al., 2010). However, our understanding of student expectancy and how returners and direct-pathway students may differ in their expectancy would be strengthened by the use of a multi-item validated scale of expectancy, similar to those used for the cost and values constructs. Additionally, the measurement of student pre-PhD expectancy of success was a retrospective measure at the time of survey administration and thus may not fully capture students' experiences prior to enrolling in their degree programs. Further, retrospective accounts of student expectancy of success prior to enrolling may be influenced in a positive direction given their success and persistence in their degrees to date (Golden, 1992; Miller, Cardinal, & Glick, 1997). Finally, if expectancy of success prior to a PhD was a major factor in individuals' decisions to enroll, our measure, capturing the experiences of current students, is likely to capture only individuals with sufficiently high expectancy to decide to enroll. An understanding of these methodological limitations is important for interpreting our findings and in identifying needs for further research.

Results

Factor Analysis Outcomes

Addressing Research Question 1, the results of our exploratory factor analysis of our value scale revealed three factors that we labeled academic interest, attainment, and career utility. Reliability estimates using Cronbach's alpha for the academic interest (α=.87), attainment (α=.78), and career utility (α=.83) factors were all in an acceptable range (Gliem & Gliem, 2003; Tavakol & Dennick, 2011). The three value factors were conceptually consistent with the three types of values (not including cost) described by Eccles, though specific to the values students associate with a PhD in engineering. Our *academic interest* factor, similar to Eccles' interest-enjoyment value, reflects variables relating to students' interest in their work, expanding their engineering skills and knowledge, and the development of their professional identities. *Attainment*, aligned with Eccles' concept of attainment value, relates to students' desire to achieve personally held academic and career goals. *Career utility*, consistent with Eccles' conceptualization of utility value, includes items related to career advancement and the financially related gains of earning a doctorate in engineering. Table 3 displays the variables that loaded onto each factor and how these new factors compare to our original classifications.

Factor analysis of the cost variables suggested a multidimensional structure with three latent cost factors, all found to be reliable measures: financial (α=.74), balance (α=.88), and academic cost (α=.86). Overall, the factors generated mapped neatly onto our original

Table 3 Value Factor Loadings with Original Variable Classifications

Variable	Academic interest	Attainment	Career utility	Original category
Taking interesting courses	0.50			Interest
Doing exciting research	0.70			Interest
Learning new things	0.72			Interest
Exploring interesting topics in-depth	0.82			Interest
Learning new research methods	0.61			Interest
Further exploring passions	0.68			Interest
Gaining teaching experience	–	–	–	Interest
Establishing core interests	0.52			Interest
Fulfilling goal of obtaining PhD		0.67		Attainment
Growing as an engineer	0.52			Attainment
Benefitting others with my work	0.53			Attainment
Gaining sense of personal achievement		0.66		Attainment
Achieving high goals set for self		0.61		Attainment
Attaining status of PhD		0.74		Attainment
Realizing professional identity	0.38			Attainment
Realizing identity as a researcher/scholar	0.51			Attainment
Advancing in my career			0.71	Utility
Getting a good job			0.78	Utility
Change/establish career focus	0.36			Utility
Changing professional environment	–	–	–	Utility
Opportunities that come with PhD		0.37		Utility
Earning a higher salary			0.77	Utility
Increasing job security			0.73	Utility

categories of financial and balance costs, with the third factor, academic cost, consisting of variables originally conceived to be related to intellectual and cultural/environmental costs. Five variables were dropped from our factor analysis because they failed to load highly onto single factors, all of which were originally conceptualized to represent cultural and environmental costs in the survey. The remaining cultural/environmental variables, which included those related to difficulty forming relationships with peers and faculty and the structure of academic work, all loaded onto the *academic cost* category, which more broadly reflects issues relating to the academic program, rather than purely students' feelings of efficacy in their domains. The *financial cost* factor includes perceived challenges related to the expenses associated with doctoral study and the opportunity costs associated with taking time out of the workforce to earn a degree. *Balance cost* reflects the strain of managing academic responsibilities with other family, friend, community, and household responsibilities and feelings of regret or stress resulting from a lack of time. Table 4 displays the new factors and the original cost variable classifications.

Expectancy, Value, and Cost Outcomes

Addressing Research Question 2, we conducted a series of regression analyses to explore if returner status was significantly related to variation in students' expectancy of success, their perceived values of a PhD in engineering, and the costs associated with earning their degrees.

Expectancy of Success in the PhD The results of our ORM model of pre-PhD confidence indicated several trends. In this model, returner status was negatively associated with expectancy of success (OR = 0.57, $p=0.03$). The odds of returners indicating the highest level of confidence in their ability to complete their PhDs upon entering the program compared to the second highest level of confidence were 43 percent less than those of direct-pathway students, accounting for all other variables. Several other variables were significantly and positively associated with all student expectancy of success prior to enrolling in a PhD program: having a bachelor's in engineering (OR = 1.36, $p=0.01$) and high levels of family support regarding students' decision to pursue a PhD (OR = 1.31, $p=0.02$).

In the model measuring student expectancy of success at the time of completing the survey (current PhD confidence), returner status was not significantly associated with differing levels of confidence about the ability to complete the degree. Academic cost and advisor support were the variables most strongly related to students' current confidence in their ability to complete their doctorates. Student level of perceived academic cost was strongly negatively associated with a higher reported expectancy of success (OR = 0.36, $p<0.01$). The index score of students' ratings of their advisors' helpfulness was strongly positively associated with a higher level of expectancy of success (OR=1.66, $p<0.01$), suggesting that advisor assistance was positively related to students' confidence in succeeding, even when accounting for the academic challenges experienced. These results are shown in Table 5.

Values of the PhD Returners did not differ significantly from direct-pathway students for any of the value categories associated with earning an engineering PhD. However, age was negatively associated with the level of importance students place on career utility value ($\beta = -0.02$, $p=0.02$). Being married was significantly (and negatively) associated with career utility as well ($\beta = -0.28$, $p<0.01$). Women placed greater importance on attainment values ($\beta = 0.25$, $p=0.01$) than men (as did those students who were divorced compared to those who were never married). Underrepresented minority students more highly valued academic interest variables than their majority peers ($\beta = 0.23$, $p=0.05$). Also predictive of academic interest were career plans: those students who reported considering a career in academia or

Table 4 Cost Factor Loadings with Original Variable Classifications

Variable	Balance cost	Academic cost	Financial cost	Original Category
Tuition			0.53	Financial
Medical insurance			0.47	Financial
Reduced salary			0.68	Financial
Less financial security			0.69	Financial
Loan debt			0.55	Financial
Difficulty securing funding			0.47	Financial
Lifestyle sacrifices	0.57			Financial
Less time for community involvement	0.44			Balance
Less time for family	0.66			Balance
Less time for hobbies	0.84			Balance
Regret missed activities	0.78			Balance
Strain in friend relationships	0.43			Balance
Strain in family relationships	0.53			Balance
Limited freedom to try new things	0.55			Balance
Can't keep up with household chores	0.64			Balance
Less time for self-care	0.69			Balance
Need to re-learn material		0.54		Intellectual
Difficulty finding study groups		0.55		Intellectual
Feeling not as smart as peers		0.71		Intellectual
Feeling at different place academically		0.56		Intellectual
Spend time on topics already knew		0.46		Intellectual
Others had learned information previously		0.58		Intellectual
Feeling unable to excel on coursework		0.69		Intellectual
Need to learn new software programs		0.48		Intellectual
Can't do best academically due to time		0.46		Intellectual
New environment/culture		0.49		Cultural/environmental
Lower professional status	–	–	–	Cultural/environmental
Time away from work	–	–	–	Cultural/environmental
Maturity of peers	–	–	–	Cultural/environmental
Open-endedness of assignments		0.56		Cultural/environmental
Less structured chain of command		0.42		Cultural/environmental
Advisor treatment	–	–	–	Cultural/environmental
Difficulty forming relationships with peers		0.57		Cultural/environmental
Difficulty forming relationships with faculty		0.53		Cultural/environmental
Class participation expectations	–	–	–	Cultural/environmental

government assigned significantly greater importance to academic interest as a value of pursuing a PhD ($\beta = 0.38$, $p<0.01$; $\beta=0.19$, $p=0.03$, respectively), while those students who did not intend to work in engineering after completing their degree assigned significantly lower importance to academic interest ($\beta = -0.34$, $p=0.04$). An omnibus test measuring the collective effect of potential career plans suggested that, collectively, career aspirations were significantly ($p=0.01$) predictive of academic interest. See Table 6 for the full results of the value regression analyses.

Costs of the PhD Returners reported significantly higher financial ($\beta = 0.29$, $p=0.03$), academic ($\beta = 0.29$, $p=0.03$), and balance ($\beta = 0.48$, $p<0.01$) cost scores than direct-pathway students, suggesting returners perceived greater challenges with the financial costs, academic environment, and work/life balance issues related to pursuing a PhD even when controlling for other personal characteristics (including age) and academic experiences.

Table 5 Ordinal Logistic Regression of Pre-PhD and Current Expectancy of Success on Demographic and Academic Traits and PhD Experiences

	Pre-PhD expectancy of success			Current expectancy of success		
Variable	Odds Ratio	95% Confidence Interval		Odds Ratio	95% Confidence Interval	
Returner	0.57*	0.33	0.96	1.28	0.69	2.36
Age	1.03	0.99	1.06	1.02	0.98	1.06
Female	0.90	0.61	1.32	0.76	0.49	1.16
Underrepresented minority	1.28	0.74	2.20	1.37	0.74	2.53
Has children	1.83*	1.15	2.90	1.24	0.91	1.69
Bachelors in engineering	1.36**	1.05	1.78	1.28	0.75	2.20
Level of family support for pursuing PhD	1.31*	1.04	1.65	–	–	–
Academic cost	–	–		0.36***	0.28	0.46
Index of advisor helpfulness	–	–		1.66***	1.36	2.04
Institutional research spending per FTE				1.00	0.94	1.27
	Cut 1	−1.25		Cut 1	−1.56	
	Cut 2	0.41		Cut 2	−0.69	
	Cut 3	2.31		Cut 3	0.37	
				Cut 4	2.28	
	LR χ^2	22.50**		LR χ^2	127.78***	
	N	439		N	398	

Note: ~p<0.1, *p<0.05, **p<0.01, ***p<0.001; Institutional Research Spending in tens of thousands of dollars per full time equivalent enrollment. Cut points in this model are similar to intercepts in linear models. Each cut point serves as a threshold between low, medium, and high levels of the latent trait. Number of cut points reflect number of ordinal categories in the model minus one—Pre-PhD expectancy of success only has 3 cut points due to lack of respondents who indicated a “1” on a 5-point Likert scale for their confidence of succeeding in graduate school.

Similarly, women perceived facing significantly higher levels of difficulty related to academic ($\beta = 0.28$, p=0.01) and balance ($\beta = 0.31$, p<0.01) costs than men. Our results suggest that in this sample, underrepresented minority (URM) students had significantly lower predicted balance costs ($\beta = -0.33$, p=0.01), though we suspect this finding may be a reflection of the relatively small, nongeneralizable sample of URM students in this study. Many other variables were associated with significantly different levels of perceived costs; being employed was associated with lower predicted financial difficulty, while GPA and having successfully completed the qualifying exam were negatively associated with academic cost, and hours worked per weekend was positively associated with higher levels of balance costs. Table 7 displays the results of the three cost regression models in more detail.

Discussion

Our research focused on exploring latent constructs of the values and costs that engineering doctoral students associate with earning a PhD as well as returners’ perceptions of expectancies, values, and costs compared to those of direct-pathway students. We discuss our results with regards to these questions as well as suggest implications for engineering education and future work.

Table 6 Multiple Regression of Value Factor Scores on Demographic and Academic Traits and Future Career Plans

Variable	Academic interest	Attainment	Career utility
Returner status	0.11	−0.03	−0.11
Age	0.01	0.01	−0.02*
Female	0.12	0.25**	0.03
Underrepresented minority	0.23*	−0.03	0.06
Has children	−0.01	0.05	0.11
Part-time student	0.04	0.02	0.11
Currently employed	−0.02	0.18	0.13
Bachelor's in engineering	0.24*	0.15	−0.06
Institutional research spending per FTE	0.02	0.00	0.00
Relationship status (Single as control)			
Married	−0.22*	−0.15	−0.28**
Divorced	−0.29	0.36*	0.24
Academic career	0.38***	0.18	−0.05
Self-employed	0.15	0.11	0.11
Return to previous job	−0.04	0.10	−0.10
Work in industry	−0.06	−0.03	0.11
Work in government	0.19*	−0.01	0.15
Not work in engineering	−0.34*	−0.16	−0.20
Undecided	0.03	0.00	0.07
Intercept (Constant)	−0.76**	−0.55	0.67*
N	455	455	455
F	2.79***	1.87*	2.70***
R^2	0.09	0.05	0.10

Note: Robust standard errors applied, ~p<0.1, *p<0.05, **p<0.01, ***p<0.001. Students could select multiple options for possible career plans, and each option was coded as a dichotomous variable. Institutional Research Spending in tens of thousands of dollars per full-time equivalent enrollment. Imputed results available upon request.

Value and Cost Scales

The exploratory factor analysis revealed several latent factors of the costs and values students may consider in their decisions to enroll and persist in an engineering doctoral program. The factor structure of our value scales suggested by our analyses in this study was largely conceptually consistent with the types of values (excluding cost) suggested by Eccles' expectancy-value framework. The similarity of our originally predicted types of values and the three value factors resulting from our exploratory factor analysis were conceptually meaningful and consistent with findings of our team's earlier work (Peters & Daly, 2013).

Individual items in our cost factor analysis almost entirely held together with their original proposed classifications, but our factor analysis collapsed our original four proposed types of cost to three types. Several of the items we originally classified as challenges related to an institution's culture or environment failed to load highly on any factors. One possible explanation for these variables not holding together in a factor analysis is that these measure cultural elements that may be more institution-specific than other types of costs. Variation in culture between institutions might have prevented variables related to this concept from varying in a cohesive, consistent pattern. Overall, however, our factor analysis revealed distinct, meaningful latent cost factors that were well-aligned conceptually with the cost categories

Table 7 Regression of Cost Factor Scores on Demographic and Academic Traits and School and Work Experiences

Variable	Financial cost	Academic cost	Balance cost
Returner status	0.29*	0.29*	0.48***
Age	0.01	0.00	−0.02
Female	0.02	0.28**	0.31**
Underrepresented minority	−0.13	−0.26	−0.33*
Has children	0.06	−0.05	0.07
Part-time student	−0.07	0.10	0.14
Completed qualifying exam	−0.08	−0.30**	0.02
Institutional research spending per FTE	−0.01	0.06	−0.02
Relationship status (Single as control)			
Married	0.04	−0.08	0.18
Divorced	−0.13	0.03	−0.40
Bachelor's in engineering	0.16	−0.06	−0.09
Currently employed	−0.44**	−0.13	−0.03
Hours worked per weekend	0.02*	0.01	0.05***
Self-funded	0.30	0.00	0.14
PhD GPA (by 0.33 interval)	−0.06	−0.33***	−0.09
Intercept (Constant)	−0.12	1.863***	0.43
N	378	378	378
F	2.51*	4.32***	5.58***
R^2	0.10	0.15	0.17

Note: Robust standard errors applied, ~p<0.1, *p<0.05, **p<0.01, ***p<0.001., Institutional Research Spending in tens of thousands of dollars per full-time equivalent enrollment. Imputed results available upon request

that emerged from our team's previous work (Peters & Daly, 2013). Further, our examination of the cost scale as a distinct element of the expectancy-value framework is consistent with recent literature calling for a more nuanced understanding of the role of cost in individuals' achievement-related choices (Barron & Hulleman, 2015; Flake et al., 2015). The multidimensionality of the cost scale lends support to the argument to explore cost in greater depth beyond a single type of subjective task value in an expectancy-value model.

In addition to strong conceptual alignment between the theoretical and empirical work and our cost and value scales, which supports the validity of these scales, the generally strong levels of internal consistency within each of the cost and value scales lends further support for the reliability of our scales. Next steps should include further testing and validation of our cost and value scales. Such a study could include confirmatory factor analyses of these two scales with samples from a variety of graduate student populations.

Expectancy, Value, and Costs

Using Eccles' expectancy-value framework to guide our understanding, we hypothesized that compared to their direct-pathway peers, returning students might have different experiences in and perceptions of their doctoral programs that could affect their decisions to initially enroll and ultimately persist in their programs. We found no significant differences between expectancies of returners and direct-pathway students, once enrolled, in their anticipated ability to attain a PhD, nor were there differences in the perceived value of the doctoral degree. However, returners reported a lower expectancy of success prior to beginning their doctoral study as well as significantly higher perceived financial, academic, and balance costs than direct-pathway students during their degree programs. While perceptions of an experience do not equate to a measure of the experience itself (i.e., what is an absolute measure of the cost one experienced as a graduate student), Eccles' (2005) expectancy-value theory posits that it is these perceptions of expectancy, value, and cost that drive decision making. Thus, it is a concern to engineering education that returners perceive higher costs in their path to earning a PhD, as higher costs, combined with their lower pre-PhD expectancy of success, could deter them from pursuing a PhD or persisting in their degree programs. Given returners' experiences, they may benefit from targeted recruitment and retention efforts.

Expectancy of Success Prior to beginning a PhD, our findings suggested returners felt less confident in their ability to complete their doctoral degrees than direct-pathway students, even when controlling for prior engineering experience, family support, and other demographic characteristics. Returners' reported lower levels of pre-PhD confidence may reflect anticipation of the documented challenges of adapting to a new academic environment or difficulty with and a lack of support through the admissions process (Gardner, 2008; Prusak, 1999; Schilling, 2008). Returners and direct-pathway students may have also had different experiences in their undergraduate programs that shaped their interest in pursuing a PhD immediately upon completion of their undergraduate degrees that may continue to shape returners' expectancy of success prior to pursuing a PhD many years later. Our measure of students' current expectancy of success at the time of the survey showed no significant relationship between returner status and the reported level of confidence in degree completion, once controlling for demographic and academic traits, reported academic challenges, and advisor support. If this trend were supported in future work, it might suggest that, despite initial reservations, given equivalent academic difficulty and proper support, returners may feel equally likely to succeed in an engineering PhD program once acclimated to its demands. However, this result should not be interpreted to mean that once enrolled, returning and direct-pathway students perceive equivalent experiences. While students may be committed to persisting and feel confident in their ability to do so for a number of reasons, our results suggest returners perceive significantly higher levels of cost related to their pursuit of a PhD.

Collectively, our findings related to students' pre-PhD and current expectancies of success speak to the need for a more in-depth study of the role of expectancy of success in returning and direct-pathway students' decisions to pursue and persist in an engineering PhD. The expectancy measures used in this study, single items regarding two time points (one retrospective), likely do not fully capture the complexity of student expectancy as it factors into achievement-related choices. Additionally, this study focused only on those students who successfully enrolled (and persisted, at least until the point of survey administration) in their doctoral programs. Successful returners' lower reported expectancy of success prior to returning may suggest a lack of confidence in their ability to succeed that could prove to be a barrier for other would-be returners in pursuing a PhD.

Values While our results revealed no significant differences based on returner status for the values students associate with pursuing an engineering PhD, age was significantly and negatively associated with career utility value. This result suggests that older students (many of whom were likely to be returners) were less motivated to pursue a PhD for reasons related to advancing their careers. In our team's earlier work, returners most commonly cited utility factors, such as the ability to advance in or change the focus of their career, as motivations for pursuing a PhD (Peters & Daly, 2011, 2012, 2013). This result warrants further study and may reflect differences in study design as the original study involved in-depth, open-ended interviews with a small group of returning students and did not account for differences in age among returning students nor comparisons with the experiences of direct-pathway students. It is also worth exploring how the specific items included in our career utility factor may relate to age. The items that loaded on our career utility factor included advancing in my career, getting a good job, earning a higher salary, and increasing job security. A significantly lower rating on the collective value of these variables could reflect the fact that for older engineers with established careers in industry, further education may not guarantee greater financial security, particularly given the opportunity costs of leaving typically well-paying engineering positions to pursue further study or the often lower pay of academic careers (Schilling, 2008). Future work should include a more thorough exploration of particular types of utility value and if they may be salient for older students. In addition, it cannot be assumed that students have uniform motivations for pursuing a PhD. The quantitative approach in our current study does not allow us to explore these likely nuances in perceived value. A subsequent phase of our study will examine students' decisions to pursue a PhD in engineering in more detail through interviews conducted with both returning and direct-pathway students who vary widely in age and career experience.

Costs Results suggest that returners perceive various types of costs to be significantly more of a challenge for them than their direct-pathway peers indicate. Thus, while returners may be determined to succeed and likely possess the skills and knowledge necessary, they perceive that doing so comes with costs, in particular those related to finances; balancing school with work, family, and personal responsibilities; and navigating a different social and academic environment, all of which are consistent with literature describing a variety of challenges for returners and other underrepresented students (Gardener, 2008; Nettles & Millet, 2006; Peters & Daly, 2013; Schilling, 2008). These costs persisted even when controlling for other demographic characteristics, institutional research spending per full-time enrollment equivalent, and other elements that might be expected to reduce the level of challenge experienced (e.g., controlling for academic performance in our academic cost model). The persistently higher perceived costs for returners, even when controlling for age, suggest that there were other specific aspects of returners' experiences that contributed to their perceptions of particular challenging elements in their doctoral experiences. It is important to reiterate that while we can only measure individuals' perceptions of the costs associated with pursuing a PhD, Eccles' expectancy-value model emphasizes that it is these perceptions that ultimately factor into individuals' decisions (as opposed to a theoretical "reality" separate from perception). The subjective task values, including relative cost, an individual associates with a particular achievement-related choice, like the decision to enroll or persist in an engineering doctoral program, are shaped by a variety of individual experiences, personal identities, and social and cultural influences.

Gender and race were also associated with significant differences in participants' reported level of cost associated with pursuing a PhD in engineering. We found gender-based differences in students' perceived levels of both balance costs and academic costs, which included challenges related to adapting to the graduate school environment and culture, finding peers to work with, and doubting their abilities. This finding is consistent with past literature that suggests women in engineering face particular difficulties related to institutional inflexibility, a chilly climate, and resulting doubts in their ability to succeed (Baker et al., 2002; Brus, 2006; Gardner, 2008; Ong et al., 2011; Tonso, 2014). This same literature consistently suggests that students belonging to underrepresented racial or ethnic minority groups also face similar challenges in engineering programs. Our result, which suggests underrepresented minority students had lower perceived balance costs, should not be interpreted to discount the well-documented challenges they must overcome to succeed in their graduate programs. Instead, we see this finding as an opportunity for further study. Our sample size (targeted to capture the experiences of returners) restricted our ability to disaggregate race/ethnicity into more meaningful categories, nor did it allow us to control for institutional context, which may influence the reported experiences of underrepresented students (Hurtado et al., 2008). Additionally, given that individuals have overlapping identities related to gender, race, and returner status, future work might explore the intersectionality of these identity traits to determine how, if at all, returner status might interact with other demographic traits in a way that further influences graduate school experiences within engineering.

Implications for Education

Our results revealed significant differences in the perceptions of financial, academic, and balance costs between returners and direct-pathway students. Based on these significant differences and approaches and programming documented in the literature to mitigate such costs, we propose options that, if implemented, may help reduce the impact of these perceived costs on engineering returners. While our findings suggest returners perceive higher levels of cost associated with pursuing a PhD, both returning and direct-pathway students may benefit from many of the resources detailed in this section. For instance, perceived academic costs are associated with lower expectancy of success, even when controlling for returner status, and students from both groups who experience a high level of challenge academically would likely benefit from additional academic support.

Resources that already exist that help mitigate these costs should be highly publicized to returning students as well as potential returning students. Existing resources across universities might include fellowships, emergency funding sources, wellness programs, counseling services, and university-based childcare services. In some cases, additional supports may need to be developed such as workshops on how to apply for fellowships and grants, short courses on specific engineering software used often in graduate courses, or lists or databases of trusted cleaning and home help service providers.

Additionally, the development of a community where returners can connect could be beneficial so that they can share strategies and feel a sense of belonging in an environment where they feel different from the majority of other graduate students. The university could organize this community and facilitate meetings multiple times throughout each term. The sessions could include opportunities for returners to learn about existing resources, communicate to engineering administration about specific struggles, and network with peers. Similar groups have been developed to support women and underrepresented minority students in engineering, and are associated with a number of positive outcomes including greater commitment to engineering, higher engineering self-efficacy, the development of a number of important engineering skills, and helping students connect with a campus support and resources (Hartman & Hartman, 2003; Simmons, Young, Adams, & Martin, 2014). Returning student organizations that allow students to connect with one another and other resources on campus might help returners deal with the academic, financial, and balance costs they perceive as associated with earning a PhD and perhaps contribute to the likelihood they choose to persist in their programs.

Another implication from this study is the need to bring awareness to engineering administrators and PhD advisors that these perception differences exist. Engineering administrators could introduce programs to support returners with the awareness that this group has reported struggles in certain areas. Recognition of perception differences between direct-pathway students and returners could also impact how advisors support their graduate students. For example, if advisors are aware that returners have reported challenges related to academic costs like peer relationships, building study groups, and adjusting to a new culture, the advisor might encourage students in their research group to take courses together or could facilitate discussions on engineering practice at research group meetings to promote networking and an opportunity for returners to share their expertise. Advisors play an important role in supporting both returning and direct-pathway students (Mosyjowski, Daly, Peters, Skerlos, & Baker, 2014), a point reinforced by the very strong positive relationship between students' perceptions of their advisors' supportiveness and their expectancy of success shown in this research. Thus, this support from advisors and other mentors could help to mitigate some of the challenges that might otherwise affect students' confidence in their ability to succeed, regardless of whether they are returners or direct-pathway students.

A final implication is the need to track the returning student demographic. The results from this study suggest that returners could benefit from a number of support strategies relating to admissions, finances, work-life balance issues, the transition back into academia, and building relationships with supportive faculty and peers. However, to target such interventions, institutions need to be able to identify prospective and current returning students. One major barrier is that returner status is not currently a tracked demographic by most institutions, making any targeted outreach or support more difficult to achieve. Tracking returner status at the college or university level is an important step in being able to recruit and better support graduate returners.

Future Work

The cost and values scales developed for this study may, if further refined, be useful for understanding the costs and values associated with students' graduate school decisions more broadly. Further work refining and assessing the reliability and validity of these scales, including confirmatory factor analyses of both with new populations, represents an important next step in advancing their usefulness in other studies and with other graduate student populations. In addition to further assessment of the cost and values measures, the development and use of a more nuanced expectancy measure would also represent an important contribution and facilitate a better understanding of students' decisions to pursue and persist in engineering doctoral study.

Insight into the experiences and perspectives of those students who are able to successfully return for a PhD is an important first step in supporting engineering returners. However, there is still much work to be done. This study was not able to capture the experiences of potential returners who may wish to pursue a doctorate but are ultimately unable or unwilling to do so. It seems likely that many of the costs identified as significantly more challenging for returners may prove to be barriers for other would-be returners. Further study is needed to pinpoint what distinguishes those students who successfully return to pursue a PhD from those engineering professionals who are interested in doing so but ultimately do not. Similarly, the cross-sectional design of our study does not allow us to examine how elements of students' expectancy of success in their degree program and the associated costs and values lead to particular enrollment or persistence outcomes or how they may evolve over time. Future work in this area would provide a clearer understanding of the consequences of the higher levels of costs perceived by returners. In addition, future work is needed to explore the specific ways the past experiences of returners shape their work in their doctoral program.

Literature and theory suggest returners may bring a unique perspective but further empirical study could be useful in making the case for more concerted recruitment efforts on the part of universities and individual faculty members seeking skilled engineers and researchers.

Conclusion

While PhD-level returners represent an important group of engineering graduate students, they have not previously been widely tracked or studied. The goal of our work was to shed light on the experiences of returning students and begin to understand how engineering programs might best support these often-overlooked students. We used Eccles' expectancy-value model of achievement-related choice to explore differences in returning and direct-pathway students' expectancy of success, values, and costs associated with pursuing a PhD that may account for their choice to enroll and continue in their doctoral programs. The results of our factor analyses revealed three values factors that align with Eccles' original value categories as well as three distinct types of costs, adding nuance to how cost has been studied using an expectancy-value framework.

The results of our regression analyses of students' expectancy of success, costs, and values associated with pursuing a PhD showed that returners are more likely to express lower levels of pre-PhD expectancy of success and report higher perceived financial, academic, and balance costs. These differences between returning and direct-pathway students have potential implications for thinking about recruiting, retaining, and supporting returners. While returners did not differ significantly in the positive values they associate with earning a PhD, differences in other elements of Eccles' expectancy-value model (namely, returners' lower Pre-PhD expectancy of success and higher perceived costs) suggest that returning students may face challenges that discourage their enrollment and persistence in engineering doctoral programs. The differences in returning and direct-pathway students' experiences are particularly striking when considering this survey allowed us to capture only the experiences of students who successfully enrolled and, at least to the time of the survey, persisted in engineering graduate education. It seems likely that issues such as a lack of information about engineering doctoral programs, their admissions process, and support services available to enrolled students may discourage interested would-be returners from pursuing additional study. Given the need for highly-skilled, innovative, diverse teams of engineering researchers, continuing to learn more about returners, their motivations, and how universities can best facilitate their success is an important topic for continued research.

Appendix

Appendix A Full Text and Operationalization of Items Included in Analyses

Item name	Question text	Operationalization in analysis
Returner	What year did you complete your undergraduate degree? ____ Have you completed a Master's degree? Yes, I completed one prior to entering my current PhD program Yes, I completed one in the course of my PhD program	Returner = 1 if total of 5 or more years not enrolled in full-time study between undergrad and PhD Returner = 0 if less than 5 years not enrolled in full-time study

Appendix A (continued)

Item name	Question text	Operationalization in analysis
	No, I have not completed a Master's and do not plan to in the course of my PhD program No, but I will complete a Master's in the course of my PhD program	*See paper for full explanation of how returner status calculated*
	What year did you complete or do you plan to complete your Master's degree? ____ When did you start your PhD program? ___	
Age	What is your current age? ____	Continuous Variable
Gender	What is your gender? Male Female Other: ______	Female = 1 Male = 0 (No "Other" responses indicated)
URM	Please select all races that apply to you: American Indian or Alaska Native Asian Black or African American Native Hawaiian or Pacific Islander White Other (Please specify)	Recoded as a dichotomous variable: URM = 1 if student selected "American Indian or Alaska Native," "Black or African American," "Native Hawaiian or Pacific Islander," or answered "Yes" to "Are you Hispanic or Latino/a?"
	Are you Hispanic or Latino/a? Yes No	URM = 0 if above options not indicated
Has Children	How many children live in your household the majority of the time? 0 1 2 3 4+	Recoded as a dichotomous variable: 0 children = 0 1–4 + children = 1
Relationship Status	What is your current relationship status? Single Divorced/Separated Married or equivalent Widowed	Recoded as Dichotomous Variables (Single, Divorced/Separated, Married or Equivalent) Used "Single" as control in regression analyses (No students indicated "Widowed"),
Part-time Student/ Employed during PhD	What is your current status? (Select all that apply) Full-time student Part-time student Employed in a field related to my degree Employed in an unrelated field Not currently employed	Recoded as dichotomous variables: Part time student = 1 if "Part-time student" selected Part-time student = 0 if "Part-time student" not selected Employed during PhD = 1 if "Employed in a field related to my degree" or "Employed in an unrelated field" selected Employed during PhD = 0 if either of above options not selected

Appendix A (continued)

Item name	Question text	Operationalization in analysis
Completed Qualifying Exam	Please select each item, if any, you have already completed during your PhD program: Selected a professor to work with All required coursework Qualifying exam/Candidacy Dissertation proposal or equivalent Dissertation defense Other (please specify):_________	Recoded as Dichotomous Variable: Completed Qualifying Exam = 1 if "Qualifying exam/Candidacy indicated" Completed Qualifying Exam = 0 if "Qualifying exam/Candidacy" not selected
Bachelor's in Engineering	Was your undergraduate major/primary field of study in engineering? Yes, my degree was in engineering Yes, I had two or more undergraduate majors and at least one of them was in engineering No, but my major was in another science/math/technology field (please specify): _________ No, my undergraduate major was not in engineering or another science/math technology field (please specify): _________	Recoded as Dichotomous Variable: Bachelor's in Engineering = 1 if "Yes, my degree was in engineering" or "Yes, I had two or more undergraduate majors and at least one of them was in engineering" Bachelor's in Engineering = 0 if "No, but my major was in another science/math/technology field" or "No, my undergraduate major was not in engineering or another science/math /technology field"
PhD GPA	What is your current GPA in your PhD program, on a 4-point scale? 0.00–1.00 (E/F to D) 1.01–2.00 (D to C) 2.01–2.33 (C to C+) 2.34–2.66 (C + to B–) 2.67–3.00 (B– to B) 3.01–3.33 (B to B+) 3.34–3.66 (B + to A–) 3.67–4.00 (A– to A)	Treated as continuous by .33 grade point interval (no students indicated a GPA below a 2.34) 2.34–2.66 (C + to B–) = 2 2.67–3.00 (B- to B) = 3 3.01–3.33 (B to B+) = 4 3.34–3.66 (B + to A–) = 5 3.67–4.00 (A- to A) = 6
Hours Worked per Weekend	Do you complete work (including homework, research, and other academic duties) related to your PhD on weekends? If so, how many hours do you work on average per weekend? No Yes (Please indicate the average number):_____	Treated as a continuous variable where No = 0 hours worked on average.
At Least Partially Self-funding PhD	Please indicate your source(s) of funding for your academic program: Fellowships Research assistantship Teaching assistantship External employer covering cost of degree Loans (private or federal) Self-funded Other (Please specify):__________	Analyses only included "self-funded" responses (participants could select multiple options) Self-funded = 1 Self-funded not selected = 0

Appendix A (continued)

Item name	Question text	Operationalization in analysis
Possible Career Plans	What do you plan to do upon receiving your PhD? Please select all that you are currently considering. Return to a previous place of employment Work in industry Start my own company Work in government Pursue a Post-Doc position Work as a professor in a teaching institution Work as a professor in a research institution Work in academia as a research scientist Work in a field not related to engineering Work as a consultant I do not plan to work immediately after obtaining my degree Undecided Other (Please specify):_________	"Pursue a Post-Doc position," "Work as a professor in a teaching institution," "Work as a professor in a research institution," & "Work in academia as a research scientist" combined to create "Work in Academia"variable; "Work as a consultant" & "Start my own company" combined to create "Self-Employed" variable Variables treated as nonmutually exclusive, dichotomous where Considering a particular option = 1 Not considering an option = 0
Family Supportiveness of Pursuing PhD	Please indicate the degree to which the following group was resistant or supportive of your decision to pursue a PhD: My family Very Resistant Somewhat resistant Neither resistant nor supportive Somewhat supportive Very supportive	Very Resistant = 1 Somewhat resistant = 2 Neither resistant nor supportive = 3 Somewhat supportive = 4 Very supportive = 5
Advisor Helpfulness Index	Please rate how effectively you feel your primary advisor meets your individual needs in each of the following: Availability to meet Management style Personal supportiveness Feedback on research Assistance with academic difficulties Career Advice	Items added and averaged to create index scale: Very ineffective = 1 Somewhat ineffective = 2 Neither effective nor ineffective = 3 Somewhat effective = 4 Very effective = 5
Pre-PhD Expectancy of Success	Prior to beginning your PhD, how confident were you in your ability to successfully complete your PhD? Very unconfident Somewhat unconfident Neither confident nor unconfident Somewhat confident Very confident	Very unconfident = 1 Somewhat unconfident = 2 Neither confident nor unconfident =3 Somewhat confident = 4 Very confident = 5
Current Expectancy of Success	How confident are you now in your ability to successfully complete your PhD? Very unconfident Somewhat unconfident Neither confident nor unconfident Somewhat confident Very confident	Very unconfident = 1 Somewhat unconfident = 2 Neither confident nor unconfident =3 Somewhat confident = 4 Very confident = 5

Appendix A (continued)

Item name	Question text	Operationalization in analysis
Value	Please indicate how important each of the following factors are as benefits in earning your PhD: Changing my professional environment Taking interesting courses Fulfilling my goal of obtaining a PhD in engineering Achieving high goals I set for myself Further exploring my passions Increasing my job security Gaining teaching experience Realizing my identity as a researcher and scholar Revisiting or establishing my core disciplinary areas of interest Growing as an engineer Earning a higher salary Having the credential of a PhD that enables me to obtain certain positions and opportunities Doing exciting research Learning new research approaches and techniques Learning new things Gaining a sense of personal achievement Advancing in my career Exploring interesting topics in greater depth Attaining the status of a PhD Benefitting others with my work Changing or establishing a focus in my career Realizing my professional identity Getting a good job	Factor Scores of three latent value variables derived from value scale: Academic Interest Attainment Career Utility Original Scale: Not at all important = 1 A little important = 2 Somewhat important = 3 Important = 4 Very important = 5
Cost (Financial, Balance, & Academic Costs)	Please indicate the extent to which each item has been a challenge at any point during your graduate experience: Less time to take care of myself Maturity of peers Loan debt upon completion Strain in my relationship with family The need to learn software programs necessary for my work The need to spend time on topics I already knew about from past experience Others learning information in their undergraduate courses I had not Class participation expectations Regret about being unable to devote time to certain activities Less time for hobbies and personal interests	Factor Scores of three latent cost variables derived from cost scale: Financial Cost Balance Cost Academic cost Original Scale: Not at all challenging = 1 A little challenging = 2 Somewhat challenging = 3 Challenging = 4 Very challenging = 5

Appendix A (continued)

Item name	Question text	Operationalization in analysis
	The feeling that I am at a different place intellectually than my group members	
	The feeling that I am unable to excel on coursework	
	A new environment/university culture	
	Difficulty securing funding	
	Less time for family interactions, including children and/or a spouse	
	Less financial security	
	Cost of tuition	
	Reduction in salary	
	Inability to keep up with household responsibilities	
	Difficulty finding study groups	
	My advisor(s)' poor treatment of me	
	Less structured chain of command	
	Lifestyle sacrifices	
	Less time for community involvement	
	The need to re-learn material for some classes	
	Time away from the work world	
	Cost of medical insurance	
	Difficulty forming relationships with faculty	
	Lower professional status	
	Inability to do my best academically due to time constraints	
	Strain in my relationship with friends	
	The feeling I am not as smart as my peers	
	Limited freedom to get involved in new activities	
	Difficulty forming relationships with peers	

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