Paper ID #19066

Measuring Students' Subjective Task Values Related to the Post-Undergraduate Career Search

Dr. Samantha Ruth Brunhaver, Arizona State University

Samantha Brunhaver is an Assistant Professor of Engineering in the Ira A. Fulton Schools of Engineering at Arizona State University. Dr. Brunhaver joined Arizona State after completing her M.S. and Ph.D. in Mechanical Engineering at Stanford University. She also has a B.S. in Mechanical Engineering from Northeastern University. Dr. Brunhaver's research examines the career decision-making and professional identity formation of engineering students, alumni, and practicing engineers. In addition, she conducts studies of new engineering pedagogy that help to improve student engagement and understanding.

Dr. Cheryl Carrico P.E., Virginia Polytechnic Institute and State University

Cheryl Carrico is a Postdoctoral Research faculty member for Virginia Tech. Her current research focus relates to STEM career pathways (K-12 through early career) and conceptual understanding of core engineering principles. Dr. Carrico owns a research and consulting company specializing in research evaluations and industry consulting. Dr. Carrico received her B.S. in chemical engineering from Virginia Tech, Masters of Engineering from North Carolina State University, MBA from King University, and PhD in Engineering Education from Virginia Tech. Dr. Carrico is a certified project management professional (PMP) and licensed professional engineer (P.E.).

Dr. Holly M. Matusovich, Virginia Polytechnic Institute and State University

Dr. Matusovich is an Assistant Professor and Assistant Department Head for Graduate Programs in Virginia Tech's Department of Engineering Education. She has her doctorate in Engineering Education and her strengths include qualitative and mixed methods research study design and implementation. She is/was PI/Co-PI on 8 funded research projects including a CAREER grant. She has won several Virginia Tech awards including a Dean's Award for Outstanding New Faculty. Her research expertise includes using motivation and related frameworks to study student engagement in learning, recruitment and retention in engineering programs and careers, faculty teaching practices and intersections of motivation and learning strategies. Matusovich has authored a book chapter, 10 journal manuscripts and more than 50 conference papers.

Ms. Mitikaa Sama

Rohini Abhyankar, Arizona State University

Rohini Abhyankar is a first year graduate student at Arizona State University's Engineering Education Systems and Design doctoral program. Rohini has a Master's degree in Electrical Engineering from Syracuse University and Master's and Bachelor's degrees in Physics from University of Delhi, India. Rohini has over ten years each of industry and teaching experience.

Dr. Ruth A. Streveler, Purdue University, West Lafayette (College of Engineering)

Ruth A. Streveler is an Associate Professor in the School of Engineering Education at Purdue University. Dr. Streveler has been the Principal Investigator or co-Principal Investigator of ten grants funded by the US National Science Foundation. She has published articles in the Journal of Engineering Education and the International Journal of Engineering Education and has contributed to the Cambridge Handbook of Engineering Education Research. She has presented workshops to over 500 engineering faculty on four continents. Dr. Streveler's primary research interests are investigating students' understanding of difficult concepts in engineering science and helping engineering faculty conduct rigorous research in engineering education. In 2015, Dr. Streveler was inducted as an ASEE Fellow.

Dr. Sheri Sheppard, Stanford University

Sheri D. Sheppard, Ph.D., P.E., is professor of Mechanical Engineering at Stanford University. Besides teaching both undergraduate and graduate design and education related classes at Stanford University, she conducts research on engineering education and work-practices, and applied finite element analysis. From 1999-2008 she served as a Senior Scholar at the Carnegie Foundation for the Advancement of Teaching, leading the Foundation's engineering study (as reported in Educating Engineers: Designing for the Future of the Field). In addition, in 2011 Dr. Sheppard was named as co-PI of a national NSF innovation center (Epicenter), and leads an NSF program at Stanford on summer research experiences for high school teachers. Her industry experiences includes engineering positions at Detroit's "Big Three:" Ford Motor Company, General Motors Corporation, and Chrysler Corporation.

At Stanford she has served a chair of the faculty senate, and recently served as Associate Vice Provost for Graduate Education.

Measuring Students' Subjective Task Values
Related to the Post-Undergraduate Career Search

Introduction

Smart capable graduates continue to leave engineering degree and career pathways. To support a diverse, well-qualified engineering workforce, educators need to better understand the career choice processes of undergraduate students enrolled in engineering programs and nearing graduation. While many researchers have examined choices to engage in specific careers, few have focused on the experience of students actually acquiring a first position post-graduation. From the engineering education and career development literature,[1-3] it is known that interest in other fields account for some diversion of engineering graduates from engineering careers. Negative attitudes and feelings about the engineering career search, however, can be partially responsible as well.[4-5]

To better understand these issues, a survey of engineering students' career decision-making and preparedness was undertaken. This survey is part of the Professional Engineering Pathway Study (PEPS), a longitudinal, mixed-methods study funded by the National Science Foundation. This study takes a national perspective, collecting data from six U.S. institutions across three states, including a Western private university, a Western public university, a Midwestern private university, a Midwestern public university, and two Eastern public universities, one of which is a residential school and the other of which is a commuter school. These schools were purposively sampled for their geographic, institutional, and student body diversity, to allow for the examination of both personal and contextual (e.g., regional, institutional, disciplinary, etc.) factors that affect engineering students' career choices. Together, they enroll approximately 16,000 engineering undergraduates.[6]

The PEPS study is grounded in Expectancy-Value Theory (EVT),[7] which conceptualizes engagement in a task as a function of four subjective task values: attainment value, intrinsic value, utility value, and cost. The focus of this research paper is on the development and validation of survey measures to capture students' subjective task values (STV) related to their post-undergraduate career search. Such measures can be used by researchers, career services professionals, and educators to identify and address causes of "problematic" career attrition[4] among students. Development of these STV measures followed a rigorous, multiphase process based on guidelines outlined by various instrument development experts[8-9] to ensure adequate validity and reliability. These phases include (1) initial item generation and the assessment of content validity and face validity, (2) pilot testing, exploratory factor analysis, and item revision, and finally, (3) survey administration and assessment of model fit through confirmatory factor analysis. This paper begins with more details about the EVT framework on which the STV measures were based, and then describes the item development process and results.

Framework

The choice of Expectancy-Value Theory (EVT) is appropriate for this study as it was originally developed to help explain low enrollment rates of women in science, math, and engineering fields.[10-13] Many researchers have used this theory to examine students' choices to pursue specific careers or enroll in courses that could lead to specific careers.[14-16] EVT posits that people are more likely to engage in activities that they value. Operationalized for this study, the activity is engaging in activities related to obtaining a first position post-graduation, and the four subjective task values would be defined as follows: (1) attainment value, the perceived importance of engaging in career search-related activities, (2) intrinsic value, the perceived enjoyment in engaging in career search-related activities, (3) utility value, the perceived usefulness of engaging in career search-related activities, and (4) cost, the perceived cost of engaging in career search-related activities.

EVT has been used increasingly in engineering education research for exploring engineering student career choices.[17-19] This research has shown that values are important in students' choices to become engineers and may be important to students' choice of a first position post-graduation.[17,19] Yet, no current survey in engineering education or elsewhere addresses students' subjective task values related to engaging in career finding activities. The survey items presented in this paper were designed, tested, and validated to address this need. Going into the project, the research team anticipated several challenges. First, cost has been proven difficult to measure so much that a special session was held about measuring cost at an American Educational Research Association (AERA) meeting.[20] Several conference papers and journal articles specifically on the cost construct have been published or are in progress.[21-23] Researchers have also sometimes found the four STV constructs difficult to distinguish.[17-18] Decisions made to mitigate these concerns are documented in the methods section.

Methods

Development of the STV Measures

The PEPS survey was developed during the summer of 2016. The survey is comprised of five sections mapped to EVT and intended to capture students' attitudes, behaviors, and beliefs related to planning their initial career steps, including (1) their current plan of study, (2) undergraduate experiences, (3) knowledge, beliefs, and influences, (4) career plans and expectations, and (5) background characteristics. The "knowledge, beliefs, and influences" section includes questions in which students are asked to self-report their subjective task values (STV) related to finding a first position post-graduation.

The research team developed items for the four dimensions of the STV construct – attainment value, intrinsic value, utility value, and cost – in close consultation with published surveys utilizing EVT in education and engineering education[17-19,24-25] to ensure that the intended meaning of each dimension would be measured. Based on the difficulties measuring cost reported in prior work,[20-23] cost items were generated along two different types of cost, task effort cost (i.e., time spent) and emotional/psychological cost,[21] to increase the likelihood of producing a factor measuring some aspect of cost. All STV items were displayed as a single scale which asked respondents, "Please indicate the extent to which you agree or disagree to the following statements about your first position after graduating with your bachelor's degree(s)," on a five-point Likert (bipolar) scale, from 0="strongly disagree" to 4="strongly agree". Nunnally and Bernstein[26] recommend the use of Likert scales because they are easy to create, produce highly reliable data, and can be adapted to measure most affective characteristics. McDonald[27] suggests five-point scales when researchers expect moderate (versus extreme) responses. The choice of a

Likert scale ranging from "strongly disagree" to "strongly agree" is also consistent with other instruments measuring subjective task values.[17-18,24]

A total of 20 STV items were generated. Content validity was assessed with experts in EVT and engineering education both within and outside of the research team. Face validity was assessed by piloting a pencil-and-paper version of the scales with four summer undergraduate researchers at one PEPS institution, and by piloting an online version of the scales with 75 engineering juniors and seniors enrolled in a summer class at another institution outside of the PEPS sample. Items identified as confusing, unclear, or misaligned with the STV dimension that they were intended to measure were modified or removed from the survey. A few additional items were removed because they were identified by pilot participants as being potentially stressful or upsetting; for example, "I will feel like a failure if I don't have an offer from an employer or graduate school by the time that I graduate," which is based on language used in other surveys measuring subjective task values,[24] but was ultimately judged to be inappropriate for this topic and population. Items with low or negative correlations within a construct after reverse-coding negatively worded items on the online pilot survey were also modified or removed.

Following revisions, the survey contained 15 items to measure the four hypothesized dimensions of the STV construct. The dimensions and their items are shown in Table 1. Notably, respondents were instructed prior to seeing these items that "first position" could include employment and/or graduate/professional school to accommodate the broad range of career paths that engineering students take after graduation. This language was reflected in many of the item stems used to measure the various STV dimensions as well.

Table 1 – Items Developed to Measure STV Related to Finding a First Position

Construct: Dimension	*Item No.*	*Item Stem*
STV: Attainment Value	STV_1	Getting an offer for a job (or graduate/professional school) would make me feel good about myself
	STV_2	I will be disappointed if I haven't found a position by the time I graduate
	STV_3	It is important to me that I have a position lined up when I graduate
STV: Intrinsic Value	STV_4	I enjoy thinking about what my first position after graduation will be like
	STV_5	I welcome the task of finding a position for after graduation
	STV_6	It is exciting to plan out my next career steps
STV: Utility Value	STV_7	By spending time looking for my first position after graduation, I will increase my chances of finding one that I like
	STV_8	Looking for my first position after graduation will help me decide what I am really interested in
	STV_9	Putting effort into my search for a first position now will help me achieve my long term professional goals
STV: Cost [1,2]	STV_10	Having to line up a position for after graduation makes me feel overwhelmed
	STV_11	I find planning out my next career steps to be stressful
	STV_12	Thinking about my first position after graduation causes me anxiety
	STV_13	I am concerned that I will not have enough time to find a position before I graduate
	STV_14	I worry that the search for my first position will negatively interfere with other aspects of my life

	STV_15	When I think about the amount of effort needed to line up a position for after graduation, I feel panicked

[1] Items STV_10 through STV_12 were designed to measure task effort cost (i.e., time spent).
[2] Items STV_13 through STV_15 were designed to measure emotional/psychological cost.[21]

Exploratory Factor Analysis

Factor analysis of the STV scale followed the procedure outlined by McCoach, Gable, and Madura,[28] which recommends establishing the preliminary factor structure of an instrument using exploratory factor analysis (EFA) on one sample, and then subjecting the revised instrument to a more rigorous test of the factor structure using confirmatory factor analysis (CFA) on a new sample. Exploratory factor analysis is an item-reduction technique wherein a factor structure that explains the most variance in the response pattern across items in the fewest number of common factors is identified. Each factor represents single, unidimensional construct which represents a unique dimension within the latent construct being measured.[28]

Data for the EFA analyses were collected as part of a pilot survey with engineering students at a large, southwestern public university outside of the PEPS sample over a two-week period in August and September of 2016. Recruitment emails to participate in the online survey were sent to students by the directors of student services in each engineering program at the university. Students could choose to enter a drawing for one of twenty $20 Amazon gift cards as a thank you for participating. The order in which items were shown on the STV scale was randomized to help reduce bias that can result from the order in which items are presented.[29] A total of 581 responses were collected, including 573 respondents who were engineering students at this institution. Most students (78%) were juniors and seniors since the recruitment email specifically targeted these classes based on the overall goals of the project, however, some first-year and sophomore students also responded. Students of all class levels were retained for the analysis. A total of 400 students provided complete responses to the STV items. Ten students were eliminated from the sample because their responses were judged to be invalid, i.e., they rated themselves the same way on every item in the STV scale even though it is unlikely that an individual would rate themselves as all “low” or all “high” on the attainment value, intrinsic value, utility value, and cost dimensions. The final sample size (n=390) was determined sufficient for conducting EFA, for which at least 10 respondents per item is recommended.[28]

Prior to EFA analysis, the skewness and kurtosis of the items were checked to ensure that the assumption of multivariate normality was not violated (i.e., that the absolute value of the skewness of each item did not exceed 2, and that the absolute value of the kurtosis of each item did not exceed 7).[30] EFA also assumes that the correlation matrix for a given scale is factorable. The research team therefore looked at the inter-item correlation matrix for the STV scale to ensure that the items within a hypothesized dimension were weakly related to items in other dimensions but strongly related to each other (r=0.3-0.6).[28]

Once the assumptions of EFA were met, the Kaiser-Meyer-Olkin (KMO) test and the Bartlett’s test for sphericity were performed to test the suitability of the data for factoring. The KMO test measures the degree of common variance among items as a function of partial correlations; variables that share a common factor will have a small partial correlation and a high KMO score, with scores above 0.8 considered desirable.[28] The Bartlett’s test evaluates whether the correlation matrix of a given scale differs significantly from the identity matrix in which items are not correlated at all (i.e., no dimension reduction is possible). A significant test result ($p<0.050$), in which case this hypothesis would be rejected, provides support that the data is factorable.[28]

Three methods were used and compared to determine the number of factors to extract for each scale: the Kaiser's criterion method, the scree test, and parallel analysis. Eigenvalues represent the variance in the items explained by a factor. Kaiser's criterion method extracts all factors with eigenvalues greater than 1, and can therefore over-extract factors when there are many items.[28] The scree test plots the eigenvalues for each factor against the cumulative number of factors and shows the approximate point (known as "the elbow") at which adding more factors to the data does not explain any meaningful additional amount of variance.[28] Yet, in many cases, scree plots can be difficult to interpret. Alternatively, parallel analysis calculates many random datasets of the same dimensions of the data set under analysis, calculates an eigenvalue for each item in each random data set, and then compares eigenvalues from the "real" and "random" datasets, keeping factors in the real dataset with eigenvalues larger than the 95th percentile eigenvalues from the random dataset.[28] Often these three approaches do not agree about the number of factors that should be extracted. There is a consensus in the social science literature that parallel analysis should be used in such scenarios,[28] although all approaches should also be informed by theory. For this analysis, the research team used parallel analysis and theory to determine the number of factors, and then confirmed this number with Kaiser's criterion method or the scree test.

Factor extraction was performed in Mplus using the maximum-likelihood (ML) technique which allows for measurement error in the data unlike other techniques which assume that all variance in a response pattern can be explained by the extracted factors and that there is no error in measurement.[28] Fabrigar and colleagues declared the ML technique as the best choice for EFA if data is approximately normal since it provides model fit indices and other information not typically provided by other methods that can be used in the comparison of competing models to each other.[31]

The factor structure was rotated to improve the interpretability of factors. Rotation is a procedure in which the factors are rotated to achieve a simpler (and therefore, more interpretable) factor structure.[28] An oblique (versus orthogonal) rotation technique was used based on the assumption that factors within a scale may be at least somewhat correlated. McCoach et al.[28] suggests starting with an oblique rotation and considering an orthogonal rotation if factor correlations are small (0.3 or lower). Oblimin rotation was selected as the oblique rotation technique, as recommended by Kim and Mueller.[32]

A "strong" factor structure in EFA is one in which all items have high loadings on a single factor and low loadings on all other factors. Thus, in this analysis, items were retained on a factor if they had a factor loading greater than 0.4 on that factor and less than 0.3 on all other factors.[28] Once the final factor structure was obtained, the research team evaluated each factor based on its number of items and its item communalities. Factors of at least 3-5 items were preferred, as a factor with three or more items is generally considered more reliable.[28] In addition, items were checked for communalities (the extent to which an item correlates with other items in the same factor) in the moderate to high range (0.4 and above). Communalities lower than 0.4 may indicate a low-performing item or the presence of an additional factor.[28] For these reasons, factors with fewer than three items and/or items with low communalities were examined and considered for item modification before redeploying the PEPS survey and testing the factor structure further with CFA.

Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) differs from EFA because it is a theory-driven (versus data-driven) approach. The researcher specifies the factor structure *a priori*, and the results of the CFA indicate how well the data conform to this model, as determined using fit indices. In this analysis, the CFI, the RMSEA, and the SRMR are utilized to evaluate the fit of the CFA on the STV construct. Table 2 presents these fit indices with their established levels of acceptableness. This analysis also utilizes the chi-square statistic, with a non-significant result ($p>0.050$) considered indicative of good model fit.[33]

Table 2 – Model Fit Indices for Factor Analysis[33]

Model Fit Index	*Level of Acceptableness*
CFI (comparative fit index)	$CFI \geq 0.90$ (good) $CFI \geq 0.95$ (excellent)
RMSEA (root mean squared error approximation)	$RMSEA \leq 0.10$ (good) $RMSEA \leq 0.05$ (excellent)
SRMR (standardized root mean square residual)	$SRMR \leq 0.08$

All 15 items in the STV scale were retested (some, with modification) in a survey of engineering juniors and seniors at the six PEPS institutions from September through November of 2016. Similar to the pilot, invitations to participate in the online survey were sent via email to students by the directors of student services, academic advisors, or the office of the dean of engineering. The survey remained open for a three-week period, with two reminder emails sent, at each school. Students could choose to enter a drawing for one of 100 $20 Amazon gift cards as a thank you for participating. The order in which items were shown on the STV scale was again randomized to help reduce order bias. The research team collected 2,542 responses, including 1,916 respondents who were engineering students at one of the six PEPS institutions. Of these students, 53 percent identified as seniors, 41 percent identified as juniors, and the remainder identified as first-year or sophomore students. As in the EFA analyses, students of all class levels were retained for the analysis. A total of 1,700 students provided complete and valid responses to the STV items.

CFA was performed using the ML estimator in Mplus. Output from these analyses was inspected to determine whether path coefficients from the factors to their corresponding items were high (0.4 and above) and significant ($p<0.050$) indicating that the factor and the item were related.[28] The research team also checked that the residual error variance for each item was significant ($p<0.050$), meaning that there was at least some unique variance in each item not explained by the factor and that the item and factor were not redundant.[28] As a final step, the convergent validity and discriminant validity of the STV items were assessed. Convergent validity is how well the items within each factor are correlated. It is measured by the average variance extracted (AVE), which is the proportion of variance in a set of items that can be explained by a latent construct (or a dimension of a latent construct) as opposed to measurement error. A construct is considered as having convergent validity if it has an AVE value of 0.50 or above.[35] Discriminant validity is how well the items within a factor relate more strongly to each other than they do to items in other factors. It is determined by examining the factor correlation matrix, wherein correlations between factors should not exceed 0.85.[28]

Lastly, the internal consistency for each factor included in the CFA model was evaluated. Internal consistency addresses the variation in individual responses within the set of items measuring a construct, or in other words, whether a set of items will consistently load onto the same factor.[28] Cronbach's coefficient alpha was used to evaluate the internal consistency of factors with three or more items. The minimum acceptable level for alpha in research is 0.7, although higher levels of 0.8 and above are considered desirable.[34]

Results

Exploratory Factor Analysis

As previously noted, EFA on the STV scale related to finding a first position post-graduation was performed using data from the pilot survey. Correlations between items ranged from 0.23 to 0.65, indicating that some items might not be good indicators of the STV construct as written. In addition, while the skewness and kurtosis for most scale items had absolute values of less than 1 and 3, respectively, one item, STV_1, "Getting an offer for a job (or graduate/professional school) would make me feel good about myself," had a skewness value of -1.705 and a kurtosis value of 3.575, indicating a non-normal distribution. However, these values were still within the assumptions of multivariate normality for factor analysis using the ML technique, and both the KMO test (score=0.84) and the Bartlett's test (p=0.000) determined the data to be factorable. EFA on the STV scale therefore proceeded as planned.

Two models, a three-factor model and a four-factor model, were extracted based on conflicting results from the various methods available for determining the number of factors to extract. Parallel analysis and the scree test supported a three-factor solution, while Kaiser's criterion method and EVT theory supported four factors. Both models showed correlations between factors ranging between -0.43 and 0.34, supporting the choice to use an oblimin oblique rotation in which factors are assumed to have some correlation.

The four-factor model produced an attainment value factor with two items (STV_2 and STV_3), an intrinsic value factor with three items (STV_4 through STV_6), a utility value factor with two items (STV_7 and STV_8), and a cost factor with six items (STV_10 through STV_15). Two items, STV_1, "Getting an offer for a job (or graduate/ professional school) would make me feel good about myself," and STV_9, "Putting effort into my search for a first position now will help me achieve my long term professional goals," did not load onto the attainment value or utility value factor, respectively, as expected. This may be due to the non-normal response pattern seen in STV_1. Both items also had standard deviations of less than 1, which further indicate an inability to discriminate among participants on these items.

Applying a three-factor model to the data produced the same attainment value, intrinsic value, and cost factors as the four-factor model. None of the three utility value items (STV_7 through STV_9) were retained in the three-factor model. Table 3 shows the factor loadings and communalities for the 12 items in the three-factor model. A chi-squared difference test of nested models was performed[36] and revealed that the three-factor solution comprised a better fit to the data than the four-factor solution (χ^2=14.35, df=7, p=0.045).

Table 3 – Results of Three-Factor Model for STV Related to Finding a First Position

Item No.	*Item Stem*	*Factor 1: Attainment Value*	*Factor 2: Intrinsic Value*	*Factor 3: Cost*	*Commun-alities*
STV_2	I will be disappointed if I haven't found a position by the time I graduate	0.781			0.644
STV_3	It is important to me that I have a position lined up when I graduate	0.829			0.674
STV_4	I enjoy thinking about what my first position after graduation will be like		0.748		0.566
STV_5	I welcome the task of finding a position for after graduation		0.567		0.348
STV_6	It is exciting to plan out my next career steps		0.808		0.645
STV_10	Having to line up a position for after graduation makes me feel overwhelmed			0.787	0.611
STV_11	I find planning out my next career steps to be stressful			0.743	0.602
STV_12	Thinking about my first position after graduation causes my anxiety			0.840	0.645
STV_13	I am concerned that I will not have enough time to find a position before I graduate			0.695	0.479
STV_14	I worry that the search for my first position will negatively interfere with other aspects of my life			0.507	0.352
STV_15	When I think about the amount of effort needed to line up a position for after graduation, I feel panicked			0.790	0.666

The three-factor solution accounted for 57 percent of the variance in the items measured. The communalities for the items in this model ranged from 0.34 to 0.67, meaning that between 34 and 67 percent of the variance in each item was explained by the three factors. Two items had communalities less than 0.40: STV_5, "I welcome the task of finding a position for after graduation, and STV_14, "I worry that the search for my first position will negatively interfere with other aspects of my life." Rather than eliminate or rewrite these items, however, they were flagged for closer inspection in the CFA.

The two items omitted from the EFA model due to poor factor loadings, STV_1 and STV_9, were rewritten prior to deployment of the survey to the PEPS institutions. In the case of STV_1, while some research suggests that it is possible to retain a factor with only two items if the items are highly correlated,[37-38] more items typically lead to better validity and reliability. STV_1 and STV_9 were thus modified slightly in the hopes of increasing their loadings on their hypothesized factors and achieving attainment value and utility value factors of at least three items. Table 4 illustrates the changes made to these items.

Table 4 – Changes to the STV Items after Pilot Testing

Item	*Version*	*Item Stem*
STV_1	Original	Getting an offer for a job (or graduate/professional school) would make me feel good about myself
	New	Finding a position before I graduate is necessary for me to feel good about myself
STV_9	Original	Putting effort into my search for a first position now will help me achieve my long term professional goals
	New	Putting effort into my search for a first position now will help me determine what to do with my life

Confirmatory Factor Analysis

A CFA of all four hypothesized STV factors was run, with covariances between factors added to the model to account for the inter-correlations between them as found in the EFA. The standardized factor loadings for each factor were "high," exceeding 0.4, and significant ($p<0.001$). The residual error variance for each item was also found to be significant ($p<0.001$). Several changes to the model were then tested. The covariances between the attainment value and intrinsic value factors, as well as the covariance between the utility value and cost factors, were not significant ($p<0.050$) and a chi-square difference test of nested models suggested that allowing these paths to vary did not meaningfully enhance model fit ($\chi^2=3.618$, df=1, p=0.0572). The removal of STV_5 and STV_14 was also tested using the chi-squared difference test due to their low communalities in the EFA analysis. Removing both STV_5 ($\chi^2=625.73$, df=1, p=0.000) and STV_14 ($\chi^2=463.19$, df=1, p=0.000) were found to worsen the fit of the model to the data. These paths were therefore retained.

Figure 1 shows the final CFA model with four factors. Circles represent different dimensions of the latent STV construct, and squares represent the observed items. The overall fit indices for the model were CFI=0.96, RMSEA=0.047, and SRMR=0.039, indicating excellent fit. The chi-square statistic for the model ($\chi^2=404.85$, df=86, p=0.000) was significant; however, Kline notes that the chi-square statistic for sample sizes greater than 200-300 are often significant and not a good measure of model fit.[39] Modification indices, used in CFA to re-specify a model to improve fit,[28] suggested no additional possible improvements. Correlations between the four factors ranged between -0.54 and 0.44, providing evidence of discriminant validity (i.e., that the items are not overly related to other dimensions of the STV construct that they are not intended to measure). AVE scores for the attainment value, intrinsic value, and cost factors ranged between 0.50 and 0.61, providing evidence of convergent validity for these factors (i.e., that the items measure the dimensions of the STV construct that they intend measure). The AVE score for the utility value factor was 0.30, suggesting that items within the factor failed to measure the same construct even after modifying STV_9.

As a final step, the internal consistency of each factor was evaluated. Cronbach's alpha scores for the attainment value, intrinsic value, and cost factors ranged from 0.73 to 0.88, indicating acceptable internal consistency for these factors. The internal consistency for the utility value factor was 0.56, signifying poor reliability and further evidence that items in the factor did not capture the same construct.

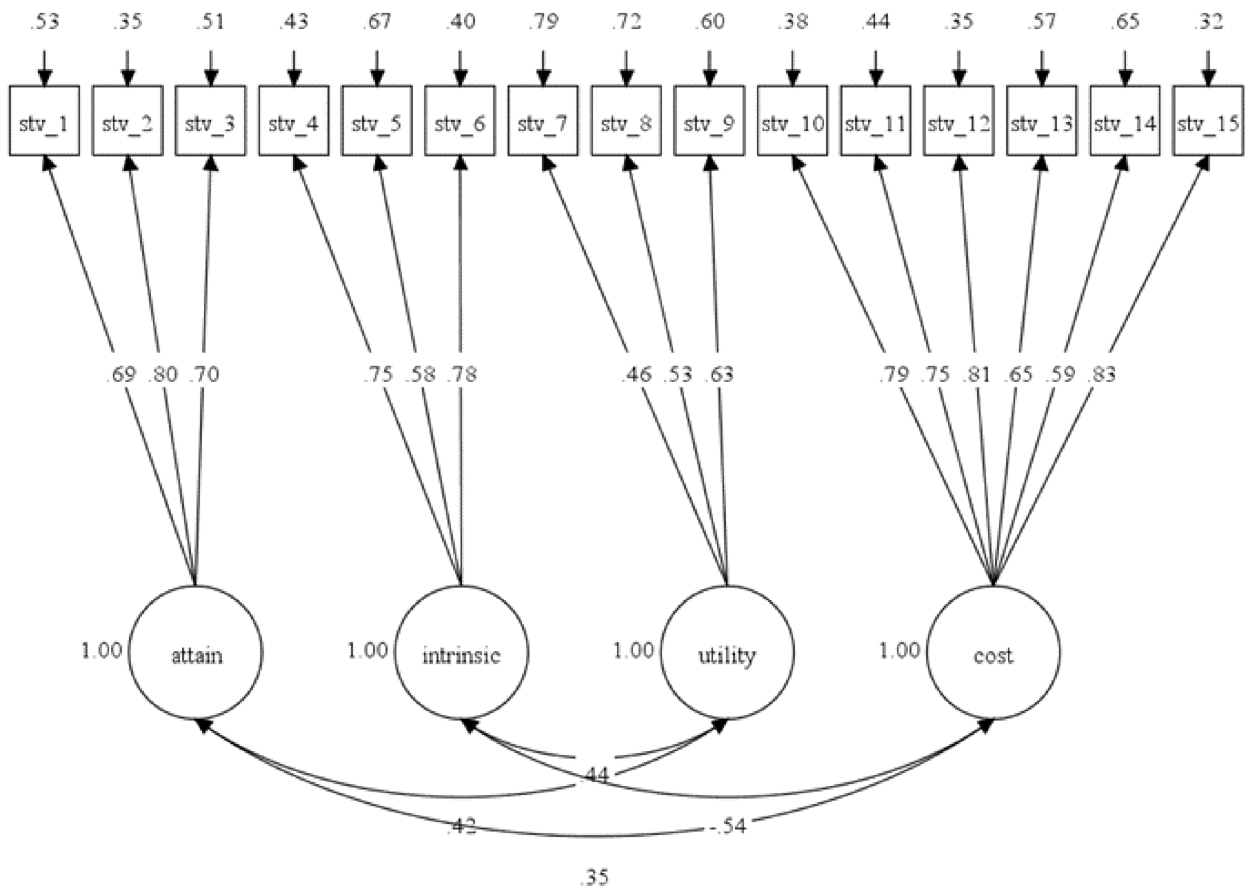

Figure 1 – CFA Results for the Four-Factor STV Model with Attainment Value (attain), Intrinsic Value (intrinsic), Utility Value (utility), and Cost (cost). All factor loadings are standardized. All paths are significant (p<0.001). Image generated in Mplus.

Conclusions

Using Expectancy-Value Theory (EVT) as a framework, a survey was designed to measure students' subjective task values (STV) related to finding a first position post-graduation. A rigorous development process was taken to iteratively develop items by testing a hypothesized factor structure. Three dimensions of STV emerged from the analysis with good validity and reliability. Somewhat surprisingly, these dimensions included cost (in addition to attainment value and intrinsic value), which previous EVT studies have noted difficulty with measuring. All six cost items, including three items intended to capture task effort cost and three items intended to capture emotional/psychological cost, loaded onto a single factor in both the EFA and CFA analyses. A fourth factor, utility value, was unsupported by the analysis. Low inter-item correlations, factor loadings, average variance extracted, and Cronbach's alpha suggest that the items used to measure utility value were poorly written. Post hoc examination of the items by the research team revealed perception of time may have been a confounder. While one item, STV_7, focused on the usefulness of the post-undergraduate career search for finding a desirable first positon – a short-term goal – the other items, STV_8 and STV_9, focused on the usefulness of the search for finding out what one is really interested in and figuring out what to do with one's life. These latter goals are, arguably, longer-term and may or may not be perceived by students as within their immediate locus of control. Further study is needed to better understand the ways in which students see the career search as beneficial.

Although the measures developed for this study explain a large portion of the variance in the STV construct, further improvement may be possible. Since the PEPS study for which these measures were created is longitudinal, there is an opportunity to follow up with the juniors who participated in this study in the upcoming academic year, to revise the utility value items and retest the factor structure. Future work could also focus on generalizing these measures to a larger sample of engineering students, as well as testing their applicability to different populations, such as by gender, class standing, and institution type.

Within the PEPS study, these measures will be used to understand and explore how the feelings of engineering juniors and seniors approaching graduation are tied to the types of experiences and interactions they have as undergraduates, and particularly to those that are career related (e.g., engagement with career services, participation in internships/co-ops). The research team is also interested in how these attitudes and beliefs influence students' career choices. Results from this research will be shared with the PEPS partner schools, and the engineering education community more generally, to help better prepare students for the career search process.

Acknowledgements

This paper is based on research supported by the National Science Foundation under Grant Nos. 1360665, 1360956, and 1360958. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the NSF. The authors acknowledge the larger PEPS study team including Helen Chen, Shannon Gilmartin, Angela Harris, and Amy Engelman. We also thank our study participants and partner school liaisons, as well as Jennifer Bekki for her advice on instrument development.

References

1. Sheppard, S., Gilmartin. S., Chen, H. L., Donaldson, K., Lichtenstein, G., Eris, O., Lande, M., & Toye, G. (2010). *Exploring the engineering student experience: Findings from the Academic Pathways of People Learning Engineering Survey (APPLES).* Seattle, WA: Center for the Advancement for Engineering Education.
2. Frehill, L. (2010). Satisfaction: Why do people give up engineering? Surveys of men and women engineers tell an unexpected story. *Mechanical Engineering, 132*(1), 38-41.
3. Greenfield, G. (2014). Career outcomes of women engineering bachelor's degree recipients. In Ed. S. J. Frueh, *Career choices of female engineers: A summary of a workshop.* Washington, D. C.: National Academies Press.
4. Margolis, J., & Kotys-Schwartz, D. (2009). *The post-graduation attrition of engineering students: An exploratory study on influential career choice factors.* Proceedings of the American Society of Mechanical Engineers International Mechanical Engineering Congress, Lake Buena Vista, FL, November 13-19.
5. Matusovich, H. M., Streveler, R., Miller, R. L., & Olds, B. A. (2009B). *Competence in engineering: A tale of two women.* Proceedings of the American Society for Engineering Education Annual Conference, Austin, TX, June 14-17.
6. American Society for Engineering Education (ASEE). (2016). *Engineering college profiles.* Washington, D. C.: American Society for Engineering Education.
7. Eccles, J. S., Adler, T. F., Futterman, R., Goff, S. B., Kaczala, C. M., Meece, J. L., et al. (1983). Expectancies, values, and academic behaviors. In J. T. Spence (Ed.), *Achievement and achievement motivation*. San Francisco, CA: W. H. Freeman.

8. Messick, S. (1995). Validation of psychological assessment: Validation of inferences from persons' responses and performances as scientific inquiry into score meaning. *American Psychologist, 50,* 741-749.
9. Moskal, B. M., Leydens, J. A., & Pavelich, M. J. (2002). Validity, reliability and the assessment of engineering education. *Journal of Engineering Education*, *91*(3), 351-354.
10. Dickhauser, O., & Stiensmeier-Pelster, J. (2002). Gender differences in computer work: Evidence for the model of achievement-related choices. *Contemporary Educational Psychology, 27*(3), 486-496.
11. Eccles, J. S., Wigfield, A., Harold, R. D., & Blumenfeld, P. (1993). Age and gender differences in children's self and task perceptions during elementary-school. *Child Development*, *64*(3), 830-847.
12. Fredricks, J. A., & Eccles, J. S. (2002). Children's competence and value beliefs from childhood through adolescence: Growth trajectories in two male-sex-typed domains. *Developmental Psychology, 38*(4), 519-533.
13. Simpkins, S. D., Davis-Kean, P. E., & Eccles, J. S. (2006). Math and science motivation: A longitudinal examination of the links between choices and beliefs. *Developmental Psychology*, *42*(1), 70-83.
14. Eccles, J. S., Barber, B. L., & Jozefowicz, D. (1999). Linking gender to educational, occupational, and recreational choices: Applying the Eccles et al. model of achievement-related choices. In Eds. W. B. Swann, J. H. Langois, & L. Albino, *Sexism and stereotypes in modern society: The gender science of Janet Taylor Spence.* Washington, D. C.: American Psychological Association.
15. Frome, P. M., Alfeld, C. J., Eccles, J. S., & Barber, B. L. (2008). Is the desire for a family-flexible job keeping young women out of male-dominated occupations? In Eds. H. M. G. Watt & J. S. Eccles, *Gender and occupational outcomes: Longitudinal assessments of individual, social, and cultural influences*. Washington, D. C.: American Psychological Association.
16. Wigfield, A., & Eccles, J. S. (2000). Expectancy-value theory of achievement motivation. *Contemporary Educational Psychology, 25*(1), 68-81.
17. Brown, P., & Matusovich, H. (2013). *Unlocking student motivation: Development of an engineering motivation survey.* Proceedings of the American Society for Engineering Education Annual Conference, Atlanta, GA, June 23-26.
18. Li, Q., McCoach, D. B., Swaminathan, H., & Tang, J. (2008). Development of an instrument to measure perspectives of engineering education among college students. *Journal of Engineering Education, 97*(1), 47-56.
19. Matusovich, H. M., Streveler, R. A., & Miller, R. L. (2010). Why do students choose engineering? A qualitative, longitudinal investigation of students' motivational values. *Journal of Engineering Education*, *99*(4), 289-303.
20. Bong, M. (2016). *Extending the Expectancy-Value Model: Definitions and functions of cost in students' choice, engagement, and performance*. Paper session presented at the Annual Meeting of the American Educational Research Association, New Orleans, LA, April 24-28.
21. Anderson, P. N. (2000). *Cost perception and the Expectancy-Value Model of Achievement Motivation*. Paper presented at the Annual Meeting of the American Educational Research Association, Washington, D. C., April 8-12.
22. Flake, J. K., Barron, K. E., Hulleman, C., McCoach, B. D., & Welsh, M. E. (2015). Measuring cost: The forgotten component of expectancy-value theory. *Contemporary Educational Psychology*, *41*, 232-244.
23. Barron, K. E., Hulleman, C. S., Flake, J. K., Kosovich, J. J., & Lazowski, R. (2016). *Moving from an expectancy-value model of motivation to an expectancy-value-cost model of motivation.* Paper presented at the Annual Meeting of the American Educational Research Association, Washington, D. C., April 8-12.
24. Battle, A., & Wigfield, A. (2003). College women's value orientations toward family, career, and graduate school. *Journal of Vocational Behavior*, *62*(1), 56-75.
25. Eccles, J. S., & Wigfield, A. (1995). In the mind of the actor: The structure of adolescents' achievement task values and expectancy-related beliefs. *Personality and Social Psychology Bulletin, 21*(3), 215-225.
26. Nunnally, J. C., & Bernstein, I. H. (1994). The assessment of reliability. *Psychometric Theory*, *3*(1), 248-292.
27. McDonald, J. A. L. (2000). *The optimal number of categories for numerical rating scales. Ph.D. dissertation.* Denver, CO: University of Denver.
28. McCoach, D. B., Gable, R. K., & Madura, J. P. (2013). *Instrument development in the affective domain*. New York, NY: Springer.
29. Krosnick, J. A., & Alwin, D. F. (1987). An evaluation of a cognitive theory of response-order effects in survey measurement. *Public Opinion Quarterly*, *51*(2), 201-219.
30. Mardia, K. V. (1970). Measures of multivariate skewness and kurtosis with applications. *Biometrika*, 519-530.
31. Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, *4*(3), 272-299.

32. Kim, J. O., & Mueller, C. W. (1978). *Introduction to factor analysis: What it is and how to do it.* Beverly Hills, CA: Sage.
33. Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1-55.
34. Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16*(3), 297-334.
35. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50.
36. Muthén, L. K., & Muthén, B. O. (2017). *Chi-square difference testing using the Satorra-Bentler scaled chi-square*. Retrieved from www.statmodel.com/chidiff.shtml.
37. Worthington, R. L., & Whittaker, T. A. (2006). Scale development research: A content analysis and recommendations for best practices. *The Counseling Psychologist*, *34*(6), 806-838.
38. Yong, A. G., & Pearce, S. (2013). A beginner's guide to factor analysis: Focusing on exploratory factor analysis. *Tutorials in Quantitative Methods for Psychology*, *92*(2), 79-94.
39. Kline, R. B. (2015). *Principles and practice of structural equation modeling.* New York, NY: Guilford Publications.