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The Development of a Measure of Engineering Identity

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The Development of a Measure of Engineering Identity

This research paper describes the recent development of items to measure post-secondary students' engineering identity. Engineering identity is a particular type of role identity that students author during their experiences in engineering, typically in college. This paper draws upon a subject-related role identity framework that focuses on students self-beliefs of their interest, performance/competence, and recognition within engineering. First, a pilot survey of 371 first-year engineering students was conducted at three institutions in the U.S. during the spring semester of 2015. An exploratory factor analysis (EFA) was performed to examine the underlying structure of the piloted questions about students' engineering identity. The developed items were used in a subsequent study deployed in the fall semester of 2015 that measured more than 2500 first-year engineering students' attitudes and beliefs at four institutions in the U.S. The data on engineering identity measures from this second survey were analyzed using confirmatory factor analysis (CFA). The results indicated that the developed measures do extract a significant portion of the average variance in the latent constructs and the internal consistency of the measures (Cronbach's α) fell within the acceptable and better range. The development of these items provides new measures for engineering education researchers to more deeply explore the underlying self-beliefs in students' engineering identity formation.

Background

Engineering identity has been shown as a significant indicator of educational and professional persistence in multiple quantitative and qualitative studies[1–8]. These prior investigations of engineering identity have focused on whether students consider or see themselves as an engineer as well as the qualities that students cite are needed to be an engineer. Other work has focused on the discourse students use to develop and identify as engineers in practice[9–11]. This discourse is part of the internal and external dialog that students use to author their identities as engineers. However, these studies have not focused on the internal states and students' self-perceptions that impact how students report an engineering role identity.

Drawing on the prior qualitative work of Gee[12]; Carlone[13] and Johnson[14]; and Shanahan[15], Hazari and colleagues[16] developed a quantitative measure of physics identity. This measure has been used to understand students' STEM career choices[16,17]. Additional work has been conducted to expand this original quantitative instrument to measure math and science identities[18–20]. The physics and math measures have been used in several large-scale, nationally representative studies to understand the impact of these identities on students' choice of a STEM major in college[18,19,21–23].

These measures of students' subject-related role identities are comprised of three constructs including students' perceptions of their own: performance/competence beliefs (i.e., beliefs in their ability to perform well and understand concepts), interest in the subject, and feelings of recognition (i.e., beliefs that they are seen as a good student in the subject by peers, parents, and teachers) as being the type of person that can do a particular subject. In prior modeling work, students' performance/competence beliefs in both math and physics were weak direct predictors of identifying as the type of person that can do a particular STEM subject[19]. When mediated by students' perceptions of interest and recognition, these constructs reliably capture students' perceptions of themselves and are predictively valuable for understanding career choices. This prior work highlights the importance of understanding students' identity with subjects with which they have direct experience like math and physics for engineering choice in college; however, it does not directly measure students' perceptions of their engineering identity.

This work describes the development of an engineering identity instrument from this basis of prior instruments to measure math, science, and physics identities. To develop a new instrument to measure engineering identity, I drew upon the historical traditions of role identity as framed in psychological and sociological literature as well as the application of this theory in science education. The basis of role identity from prior literature is described in the next section.

Theoretical Framework

Role identity is the meanings that the individual attaches to the context of a social and cultural role. An individual has as many selves or identities as he or she has groups of people with which he or she interacts[24]. Some identities become more salient based on the particular context and social situation in which an individual is immersed. This framing of identity comes from social identity theory and symbolic interactionism. Symbolic interactionism is the meanings that individuals develop and rely on as a part of social interaction. In this key sociological theory, when a person has claimed an identity, he/she acts on the basis of that identity, and he/she attempts to fit their lines of action with others in that community to accomplish their goals[25]. There are different emphases in identity theory that focus on how individuals define themselves in relation to social structures, how individuals' internal dynamics influence behavior, and how identities are maintained and manifested in face-to-face interactions[24,25]. My work draws on the work of Burke and his associates[26,27] to understand how the internal dynamics and roles that individuals ascribe to themselves impact behavior.

For engineering students, I am interested in how they describe how they see themselves as the type of people that can do engineering as well as feel like engineering is "for them." Identifying as an engineer matters for students' academic and personal development[28–31], retention[32–34], and incorporation into the larger engineering community[1,35,36]. In their process of engineering identity development, students must negotiate the roles they play within the community of engineering as a discipline, in groups with their peers, and within the classroom. Engineering students must author individual identities that map to the group identity of an engineer. Development of an engineering identity requires legitimate participation and recognition within that social sphere[37]. Based on prior work in science education and a symbolic interactionism approach to understanding engineering role identity, the construct of identity, in our framework, is based on three measurable dimensions of students' beliefs about their performance/competence, the recognition they receive from others, and their interest in engineering. These are not the only identities that an individual may hold, but they capture a students' subject related identity within engineering. A representation of this framework can be found in Figure 1.

Recognition plays a significant part in identity development and has more recently become a focus in science identity research. A student's perception of how others view him or her is vitally important to how that student sees himself or herself. These recognition messages are important early on in students' careers from parents and teachers[38–41], but also during engineering identity development in college through instructors and peers. Tonso's[36,42] ethnographic studies of an elite engineering program provided examples of how female students who showed great skill in engineering but were not recognized by their peers and professors had weaker identities as engineers and did not feel like they belonged in engineering.

Interest is also a vital component of engineering identity development. An individual's interests defined as a "person's likes, preferences, favorites, affinity toward, or attraction to a subject, topic, or activity[43]," have a rich theoretical basis as a fundamental construct in models for human learning[44]. Vygotsky[45] claimed "thought… is engendered by motivation, i.e., by our desires and needs, our interests and emotions." For these reasons, interest in engineering as a subject has been an important part of behavioral research within engineering education[46–48]. Interest plays a key role in whether or not students want to take on the role identity as an engineer.

Additionally, students' performance/competence beliefs have also been shown to be an important part of identity development and engineering choice. This idea is related to students' self-efficacy beliefs, which have been shown to be a significant positive predictor in engineering persistence[49,50]. Performance/competence beliefs are broader than self-efficacy, which has been traditionally measured as task-specific attainment[51]. Students' beliefs about their ability to perform the practices of their discipline and understand the content of their discipline – whether science, math, or engineering – has an impact on their ability to see themselves as the kind of person who can legitimately participate in these areas[52].

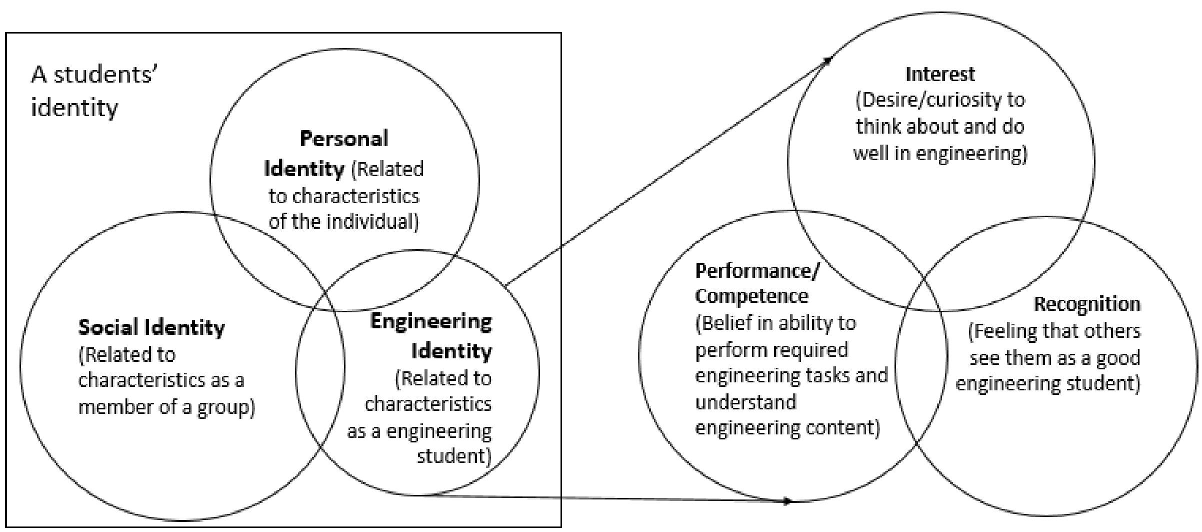

Figure 1. Framework for students' identification with engineering adapted from Hazari et al.[16]

These three factors (recognition, interest, and performance/competence) comprise the identity measures developed in this work and are consistent with prior literature from psychology, sociology, science education, and engineering education. This paper describes the question development and provides validity evidence for these items through an exploratory pilot study of the factors as well as a larger, second study using confirmatory factor analysis. The results of this work provide an instrument to measure students' self-reported engineering role identities early on in their post-secondary careers (first- and second-year students). The results of this study are only generalizable to the student populations that were surveyed which were students enrolled in an introductory engineering course.

Development of Engineering Identity Measures

Based on my prior research on STEM identities that impact engineering career choice as well as the theoretical framework of subject-related role identities as described in the previous section, I developed items to measure engineering identity for early post-secondary students. The items for these measures capture three constructs of identity: students' feeling of recognition by others; students' interest in the subject; and students' beliefs about their performance/competence in the subject area. In prior studies with late secondary and early post-secondary students, participants did not distinguish between performance beliefs (e.g., believing that they can do well in a particular subject) and competence beliefs (e.g., believing that they can understand a particular subject)[16,53]; therefore, performance/competence beliefs are measured as a single subconstruct, consistent with prior literature. These items measuring engineering identity are listed in Table 1. These self-reported items were measured by asking students to rate "To what extent do you agree or disagree with the following statements:" on an anchored scale from 0 – "strongly disagree" to 6 – "strongly agree." A seven point scale was chosen because the items are bipolar items (i.e., conceptually range from negative infinity to infinity)[54]. Additionally, the choice of an anchored scale rather than a Likert scale allowed for a more interpretable distance between each numeric response and made the assumption of continuous scales associated with maximum likelihood factor analysis more valid[55,56]. For example, the distance between a response of 1 and 2 on an anchored scale between 0 and 6 is clearer than the distance between a response of "somewhat agree" and "agree." Each student response on a Likert scale may be a different interpretation of distance, and thus, these scales should be treated as ordinal data. There may still be some issues of interpretation of distance with anchored scales, but the ambiguity is reduced by providing interval headings for each response.

Additionally, item development was not a direct translation from prior measures of physics and math identity. I added additional items based on pilot interviews with first-year engineering students conducted in the spring semester of 2015. These items were added to more richly capture aspects of engineering identity from student's own words as well include a minimum of three items per scale (preferably four) to ensure adequate specification of constructs[57].

Table 1. Items developed to measure engineering identity.

Construct	*Question*	*Statement*
Recognition	Q8Eng_d	My parents see me as an engineer.
	Q8Eng_e	My instructors see me as an engineer.
	Q8Eng_f	My peers see me as an engineer.
	Q8Eng_g	I have had experiences in which I was recognized as an engineer.
Interest	Q8Eng_h	I am interested in learning more about engineering.
	Q8Eng_i	I enjoy learning engineering.
	Q8Eng_j	I find fulfillment in doing engineering.
Performance/ Competence	Q8Eng_k	I am confident that I can understand engineering in class.
	Q8Eng_l	I am confident that I can understand engineering outside of class.
	Q8Eng_m	I can do well on exams in engineering.
	Q8Eng_n	I understand concepts I have studied in engineering.
	Q8Eng_o	Others ask me for help in this subject.
	Q8Eng_p	I can overcome setbacks in engineering.

Exploratory Factor Analysis

Pilot Data

Pilot data to gather validity evidence for the newly developed engineering identity items were collected from three institutions across the U.S. In the spring semester of 2015, students in second-semester first-year engineering courses were surveyed electronically. A total of 371 students responded with valid responses. Valid responses were determined using a filter question on the survey to exclude students with non-discriminant responses. This sample size is large enough for factor analysis using the rule of thumb of at least ten students per item[58].

Methods

The R programming language statistical software system was employed to examine the engineering identity constructs[11]. First, a correlation matrix was created to ensure that items theorized to measure a single latent construct were significantly correlated. Second, a maximum likelihood exploratory factor analysis was conducted to examine how well the items on developed to measure engineering identity loaded on the theorized constructs. If the resulting factors aligned with the framework, then the data also supports the construct validity of the constructs in the framework of identity (recognition, interest, and performance/competence). A maximum likelihood factor analysis allows for explicit testing of factor loadings and correlation among factors[59]. However, if the assumption of multivariate normality is severely violated, then this model-fitting procedure can produce inaccurate results[60]. The skew and kurtosis were evaluated for each item to ensure that the assumptions of multivariate normality were not severely violated (absolute value of skewness of 2.0 or higher and kurtosis of 7.0 or higher[60,61]).

A promax (non-orthogonal or oblique) rotation was employed since the theory naturally permits inter-correlation between the constructs (i.e., the factors were not expected to be orthogonal). Because recognition, interest, and performance/competence capture different aspects of engineering role identity, I expected the factors to be related to one another. For social science research, an oblique rotation is a more realistic representation of measured pehnomena[62]. Restricting rotations to uncorrelated factors can result in inaccurate or misleading results.

Exploratory factor analysis is based on the common factor model[63]. This model postulates that each measured variable in a battery of measured variables is a linear function of one or more common factors and one unique factor. Common factors are unobservable latent variables that influence more than one measured variable in a battery and are presumed to account for the correlations among the measured variables (i.e., two measured variables are assumed to be correlated because they are influenced by one or more of the same common factors). This approach examines the common factor structure in the data without *a priori* assumptions about how the factors are constructed.

Both a scree plot and parallel analysis were used to determine the number of factors to extract in the exploratory factor analysis. A scree plot visually shows the descending values of the eigenvalues of the correlation matrix which is examined to identify the last substantial drop in the magnitude of the eigenvalues based on the number of factors. This method is subjective and sometimes does not result in a clear drop in the eigenvalues on the plot making interpretation difficult[64]. Based on recommendations by Fabrigar and colleagues[62] parallel analysis was also used. Parallel analysis compares the eigenvalues obtained from sample data to eigenvalues one would expect to obtain from completely random data to determine the number of expected factors.

Results

An examination of a correlation matrix shows that items in each theorized subconstruct are significantly correlated. Items across constructs were also correlated with coefficients in the range of 0.3 to 0.4 emphasizing the need for an oblique rotation (i.e., a rotation that allows the constructs to be related to one another. This approach is also consistent with the theoretical framework that recognition, interest, and performance/competence are related to overall subject-related role identity). Skewness of items ranged from -0.76 to -1.6 indicating non-normal distributions, but still within the assumptions of maximum likelihood factor analysis. Kurtosis ranged from 2.33 to 5.9 also indicating non-normal distributions, but still within the assumptions of maximum likelihood factor analysis[60]. To determine the number of factors, a scree plot and parallel analysis were used. Both indicated that three factors were the optimal number for this analysis.

An exploratory factor analysis of three factors was conducted on the pilot data. The factor loadings and uniqueness values for each item are shown in Table 2. Tabachnick and Fidell[65] cite 0.32 as a good rule of thumb for the minimum loading of an item, which equates to approximately 10% overlapping variance with the other items in that factor. All of them items have factor loadings much higher than 0.32 with the minimum loading with a value of 0.52. Two of the items, Q8Eng_o, "Others ask me for help in this subject," and Q8Eng_p, "I can overcome setbacks in engineering," had some cross-loading across constructs. These loadings are below the cutoff of 0.32 and are less than double the main loading; therefore, these items were not eliminated from the analysis. Uniqueness gives the proportion of the common variance of the variable not associated with the factors. It is equal to: (1 – communality), where communality is the proportion of variation in that variable explained by the factors. Communality is calculated as the sum of the squared item loadings. Item communalities, ideally, should be 0.8 or greater (meaning that 80% of the variance is explained by the number of factors for each item). In social science communalities often range from 0.4 to 0.7[66]. All of the items except for Q8Eng_g, "I have had experiences in which I was recognized as an engineer," fall within that range indicating that this item may not be a good indicator of the latent factor or may be poorly written. All items were used in the full-scale deployment of the survey in order to test the validity and reliability of the items further.

The three-factor model accounts for 71% of the variance in the items measured. The fit of the maximum likelihood factor analysis was conducted using the root mean square error of approximation (RMSEA) fit measure and Tuck Lewis Index (TLI). For RMESA values less than 0.01, 0.05, and 0.08 indicate excellent, good, and moderate fit respectively[67], and for TLI values greater than 0.90 indicate good fit[68]. The RMSEA for this model is 0.062 with the 90% confidence intervals of 0.046 to 0.077, and the TLI is 0.973 both indicating good fit.

Table 2. Results of exploratory factor analysis on engineering identity constructs.

Statement	**Factor 1 – Recognition**	**Factor 2- Interest**	**Factor 3 – Performance/ Competence**	**Uniqueness**
My parents see me as an engineer.	0.75			0.44
My instructors see me as an engineer.	0.88			0.25
My peers see me as an engineer.	0.93			0.19
I have had experiences in which I was recognized as an engineer.	0.63			0.63
I am interested in learning more about engineering.		0.87		0.23
I enjoy learning engineering.		0.97		0.05
I find fulfillment in doing engineering.		0.88		0.17
I am confident that I can understand engineering in class.			0.93	0.14
I am confident that I can understand engineering outside of class.			0.89	0.19
I can do well on exams in engineering.			0.96	0.27
I understand concepts I have studied in engineering.			0.86	0.19
Others ask me for help in this subject.	0.20		0.58	0.47
I can overcome setbacks in engineering.		0.24	0.52	0.37

Confirmatory Factor Analysis

Data

After the pilot data were analyzed, all of the items were included in a large-scale survey distribution at four institutions across the U.S. in the fall semester of 2015. Students in first-semester first-year engineering courses were surveyed on a paper-and-pencil instrument as part of a larger study. We collected 2,966 valid student responses that were digitized by the research group and audited for accuracy.

Method

Similar to methods for examining data in exploratory factor analysis, correlations between items hypothesized to measure the same subconstruct were examined for statistically significant correlations. Additionally, the data were examined for significant deviations from normality. Confirmatory factor analysis, like exploratory, assumes multivariate normally distributed items. Because the estimation is robust, some deviations from normality are acceptable, but this assumption should not be severely violated (absolute value of skewness of 2.0 or higher and kurtosis of 7.0 or higher[60,61]). Finally, the internal consistency of the items was assessed using Cronbach's alpha with coefficients of 0.70 considered acceptable for newly developed scales while values of 0.80 or higher are preferred and indicate that the items may be used interchangeably[69].

Unlike exploratory factor analysis which is a data-driven approach, in confirmatory factor analysis, the structure is specified by the researcher. Confirmatory factor analysis allows the researcher to explicitly test the hypothesis that the relationship between the observed (measured) variables and the underlying latent construct exists. The lavaan package in R was used to estimate all of the confirmatory factor analysis estimates[70]. The factor variance was fixed to one to allow the standardized estimates of each path to be estimated. Paths from the latent constructs to the measured variables were specified according to the theorized constructs and exploratory factor analysis results. Additionally, the latent factors were allowed to covary which is consistent with the oblique rotation in prior exploratory factor analysis and theorized structure.

Once the model was specified it was tested for model fit and path significance. Several fit indices were used the evaluate the model based on Byrne's suggestions[71], including chi-square (should be non-significant at the $p < 0.05$ value[71]), Comparative Fit Index (CFI) (acceptable values occur above 0.9[72]), Tucker Lewis Index (TLI) (acceptable values occur above 0.9[72]), and root mean square error of approximation (RMSEA) (values less than 0.01, 0.05, and 0.08 indicate excellent, good, and moderate fit respectively[67].

Results

An examination of a correlation matrix shows that items in each theorized subconstruct are significantly correlated. Skewness of items ranged from -0.30 to -1.5 indicating non-normal distributions, but still within the assumptions of maximum likelihood factor analysis. Kurtosis ranged from 2.09 to 4.56 also indicating non-normal distributions, but still within the assumptions of confirmatory factor analysis[60]. Construct reliability as evaluated with Cronbach's alpha was 0.77 for recognition; 0.89 for interest; and 0.88 for performance/competence. This reliability gives a better estimate of the overall reliability of an item taking into account the individual reliabilities as well as standard errors. The Cronbach's alpha indicated strong internal consistency or that items measured as a single factor grouped strongly together. Based on these ranges, the values for these items fell within the good to excellent range for a newly developed scale[73].

The results of the structure of the confirmatory factor analysis model are shown in Figure 2. The figure illustrates the latent factors as yellow ovals (Recognition = Rec; Interest = Int; Performance/Competence = PC) and the measured variables as green rectangles. The arrows from the latent variables to the measured variables show the model paths with the standardized factor loadings. The curved arrows between the latent variables display the covariances between the latent constructs. These paths were added into the model to allow for the inter-relationship of these identity constructs and are consistent with the theoretical basis of question development. The arrows pictured below the measurement variables indicate the error associated with each measured variable. This error is the portion of the variance in each measurement that does not covary with the latent factor[71].

Consistent with some of the borderline questions highlighted in the earlier exploratory factor analysis, questions Q8Eng_g, "I have had experiences in which I was recognized as an engineer," and Q8Eng_p, "I can overcome setbacks in engineering," were removed from the model based on model fit and statistical significance. The other question with cross loading, Q8Eng_o, "Others ask me for help in this subject," did remain in the analysis, but had the lowest loading on the performance/competence factor of all the items developed. The model was tested with this path removed, but it did not significantly improve the fit of the model and the significant path of this measurement item onto the factor loading provides an additional dimension to the performance/competence factor.

Additionally, based on modification indices, the measurement items Q8Eng_k, "I am confident that I can understand engineering in class," and Q8Eng_l, "I am confident that I can understand engineering outside of class" were allowed to covary. Modification indices are used to respecify a model to improve the fit of the model implied matrix with the data implied matrix. These values are the amount chi-square will drop if the parameter is estimated as part of the model. The chi-square value of 3.84 is the value that should be exceeded at the alpha 0.05 level for one degree of freedom. For adding the error covariance, in this case, the modification index was the largest of all significant modification indices at 398. These values should be used with caution and only adjust the model if they are consistent with theory. In this case, the wording of Q8Eng_k and Q8Eng_l are very similar and these measurement items capture similar information about students' competence beliefs; therefore, this modification was made and the resulting model better reflects the data implied matrix.

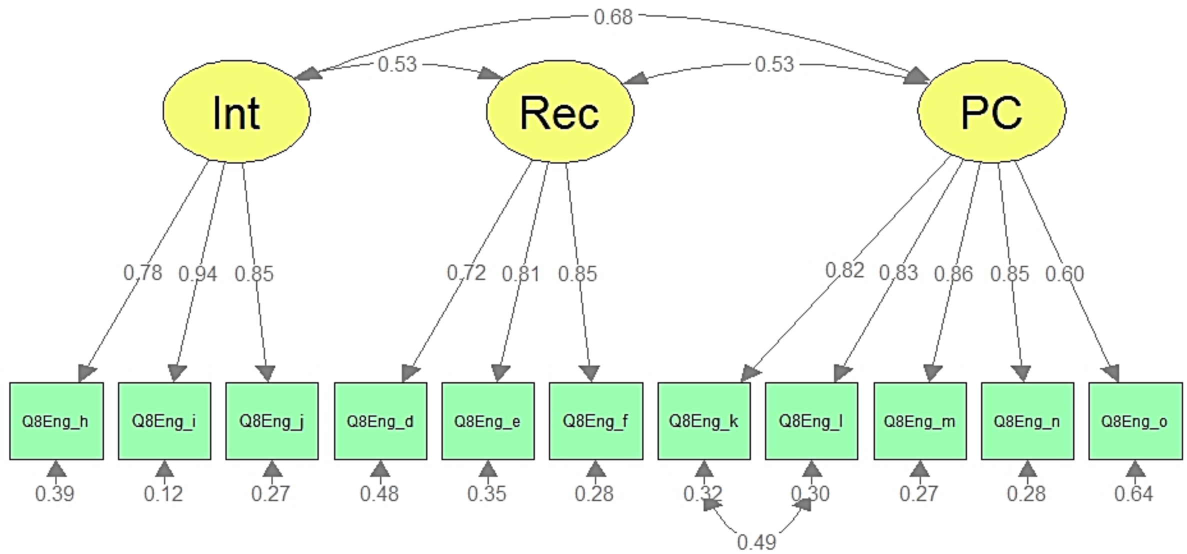

Figure 2. Confirmatory factor analysis of the latent constructs of identity: interest (Int), recognition (Rec), and performance/competence (PC) beliefs for 2790 students in first-year engineering at four U.S. institutions during the fall semester of 2015. All paths are significant at the $p < 0.001$ level. Image generated using the semPlot package in R[74,75].

The confirmatory factor analysis indicates that the data do fit the model developed. The average variance extracted (AVE) is the amount of variance that is captured by the construct in relation to the amount of variance due to measurement error[76]. In different terms, it is a measure of the error-free variance of a set of items measuring a single construct. Average variance extracted is used as a measure of convergent validity, which should be 0.50 or above[77]. For these constructs, the AVE was 0.61 for recognition; 0.82 for interest; and 0.64 for performance/competence. These results demonstrate that the items hypothesized to measure a single construct do, in fact, measure the intended construct and capture a large portion of the variance within each block of items. Discriminant validity provides evidence that measures for one latent variable are not overly rated to another latent variable and was established through multiple methods. The correlation between items of unrelated latent variables in our study is less than 0.85[71]. The overall fit indices for the measurement model were a CFI of 0.96, TLI of 0.95, and an RMSEA of 0.077. All of these fit indices indicate that the measurement variables accurately reflect the latent variables in the measurement model. The chi-square statistic ($\chi^2 = 810$; df = 40; $p < 0.001$) for this model was significant, but this is not unexpected since the sample size is so large. For sample sizes greater than 400, the chi-square statistic is not a good indication of model fit[78]. Instead, RMSEA is a better indicator of fit and is less sensitive to changes in sample size. For this model, the RMSEA indicates acceptable fit of the model.

The results of the confirmatory factor analysis indicated that some of the items used to measure engineering identity should be modified. In Table 3, are the final measurement items after comparing different factor analysis models and determining the model that best fits theory as well as the measured data. At least three questions remain for each latent variable allowing for adequate specification for future factor analysis or other advanced modeling. I offer these items as a first step in developing quantitative measures of engineering identity.

Table 3. Final items to measure engineering identity.

Construct	*Question*	*Statement*
Recognition	Q8Eng_d	My parents see me as an engineer.
	Q8Eng_e	My instructors see me as an engineer.
	Q8Eng_f	My peers see me as an engineer.
Interest	Q8Eng_h	I am interested in learning more about engineering.
	Q8Eng_i	I enjoy learning engineering.
	Q8Eng_j	I find fulfillment in doing engineering.
Performance/ Competence	Q8Eng_k	I am confident that I can understand engineering in class.
	Q8Eng_l	I am confident that I can understand engineering outside of class.
	Q8Eng_m	I can do well on exams in engineering.
	Q8Eng_n	I understand concepts I have studied in engineering.
	Q8Eng_o	Others ask me for help in this subject.

Discussion and Conclusions

The results of these two studies provide strong validity evidence for the use of these items to measure the role identity constructs of recognition, interest, and performance/competence for early post-secondary engineering students. I have described the systematic development of items from prior research, literature, theory, and qualitative pilot studies. This work highlights the iterative nature of instrument development and the importance of balancing a variety of psychometric measures in determining which items accurately measure underlying latent constructs of identity. The pilot study allowed me to explore the structure of the data as implied by student responses. Once the structure was determined, a larger study provided stronger validity evidence of the three-factor structure used for these items.

This work is a first step in creating and refining items for quantitative engineering identity measurement. These items can be used to understand how students see or do not see themselves as the type of people that can do engineering. These items were only tested with data from students in introductory engineering courses, and therefore, cannot be generalized to all engineers. While the development of these items is limited to engineering students early on in their engineering careers at four-year institutions, future work will seek to apply these measures more broadly to understand engineering role identities of students across varying types of institutions and demographics. The results do, however, suggest that these items measure a large portion of the variance in these latent factors consistent with prior studies in science and engineering education.

Much of engineering identity research has delved deeply into the narrative that students tell or the discourse that these students use to develop expertise as engineers and identify with engineering as a profession. These approaches yield thick, rich data that takes significant effort to understand and analyze. The items developed to measure engineering identity are the first of their kind to quantitatively measure students engineering identity self-beliefs. I offer these items as a way to quickly assess and broadly understand students’ engineering identity development.

These items capture an overarching picture of students' subject-level identity within an engineering context but do not replace the complex and nuanced narratives that students author as they navigate their engineering identities. Full information about these items has been included in this paper to allow the engineering education community to use these items for future research on identity which an increasingly important topic.

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