Board 435: Work in Progress: Preliminary Findings from NSF Award No. 2205033 - Research Initiation: Mapping Identity Development in Doctoral Engineering Students

Diego Alejandro Polanco-Lahoz, Texas Tech University

Diego A. Polanco-Lahoz is a Ph.D. student, from the program of Systems and Engineering Management, in the Department of Industrial, Manufacturing & Systems Engineering at Texas Tech University. He received his BS in Industrial Engineering from the Pontificia Universidad Católica de Valparaíso (PUCV). His research interests are organizational factors research, organizational assessment/performance measurement, and engineering education.

Dr. Jennifer A Cross, Texas Tech University

Jennifer Cross is an Associate Professor in the Department of Industrial, Manufacturing & Systems Engineering at Texas Tech University. She received her BS in Industrial Engineering from the University of Arkansas and her MS and PhD in Industrial and Systems Engineering from Virginia Tech, where she also served as a Postdoctoral Associate in the Enterprise Engineering Research Lab. Her research interests are organizational assessment/performance measurement, teams, performance improvement methodologies, and engineering education.

Kelli Cargile Cook, Texas Tech University

Kelli Cargile Cook is a Professor and Founding Chair of the Professional Communication Department at Texas Tech University. Previously, she served as Professor and Director of Technical Communication and Rhetoric at Texas Tech and as Associate Professor at Utah State University. Her scholarship focuses on online education, program development and assessment, and user-experience design.

Dr. Mario G. Beruvides P.E., Texas Tech University

Dr. Mario G. Beruvides is the AT&T Professor of Industrial Engineering and Director of the Laboratory for Systems Solutions in the Industrial Engineering Department at Texas Tech University. He is a registered professional engineer in the state of Texas.

Jason Tham, Texas Tech University

Jason Tham is an associate professor of technical communication and rhetoric at Texas Tech University. He is author of Design Thinking in Technical Communication (2021 Routledge) and co-author of UX Writing (2024 Routledge), Writing to Learn in Teams (2023 Parlor Press), Designing Technical and Professional Communication (2021 Routledge), and Collaborative Writing Playbook (2021 Parlor Press). He has also edited the collection Keywords in Design Thinking (2022 University Press of Colorado).

Md Rashedul Hasan, Texas Tech University

I am working on my MS in Systems and Engineering Management at Texas Tech University. I am from Bangladesh, a South Asian country known for its abundant green landscapes. After completing my master's program, I intend to pursue a Ph.D. in Industrial and System Engineering. With a focus on bridging theory and practice, I intend to uncover the factors that shape the identities of doctoral engineering students, thereby contributing to enhancing academic programs and support mechanisms. Through rigorous analysis and innovative methodologies, I aim to generate insights that will inform policies and interventions to foster a conducive environment for the growth and success of future engineering scholars.

WIP: Preliminary Findings from NSF Award No. 2205033 - Research Initiation: Mapping Identity Development in Doctoral Engineering Students

Abstract

This work in progress (WIP) paper focuses on the development and initial validation of a survey adapting the three identity scales from Godwin's (2016)[1] Engineering Identity measure – Recognition (R), Interest (I), and Competence (C) - to assess research identity formation in doctoral engineering students. This study is a product of an NSF grant (Award No. 2205033) obtained to apply user experience (UX) methods to investigate the process through which doctoral engineering students develop their research identity. This survey was conducted during 2022 and 2023 for on-site and online Ph.D. students enrolled in various engineering fields at a large research university in the United States. In addition to the three identity scales, items from the survey include demographics, self-perceptions of capability to perform in different contexts, and various curricular and co-curricular experiences, including research experiences. Validation results include exploratory factor analysis of items utilizing oblimin rotation, KMO and Bartlett's test, pattern matrix, component correlation matrix, and Cronbach's alpha measures for each identity construct. These results suggest that the survey's adaptation for research identity formation is valid and reliable. The instrument properties are further compared with the most closely related measures, including Godwin's original scales, their sources, and the expanded researcher identity measure proposed by Perkins et al. (2018)[2]. Future research and applied work can benefit from this study by considering the experiences of other doctoral students, including those in programs beyond the engineering contexts studied. This research may impact future engineering doctoral program designs and contribute to the education of generations of doctoral engineering students and scholars interested in this area.

Introduction

This WIP paper provides initial results regarding the validation of an adapted survey that measures research identity in doctoral students. The survey adapts Godwin's (2016)[1] engineering identity dimensions of recognition, interest, and competence. Likewise, other items of the survey include the demographics of participants and their current situation in the respective doctoral program, among others.

This research is part of a larger study focused on applying user experience (UX) methods[3], including surveys, to investigate the process through which doctoral engineering students develop their research identity. This larger study aims to address three important gaps in the current literature about engineering identity development. First, there is limited existing longitudinal research on engineering identity development at any level of education. Second, there is limited existing research on engineering identity development in doctoral students. Third, there is limited existing research on the process of engineering identity development, again at any level. Future research along with practical work can benefit from this study, particularly if the experiences of other doctoral students are included. The impact of this study may change engineering doctoral program designs and may contribute to the education of doctoral engineering students interested in these fields.

This paper, specifically, supports addressing the gaps regarding the formation of identity, specifically the formation of research identity, in engineering doctoral students, by providing the initial validation of survey designed to measure this identity. Both the survey tool and the other initial study results can be used to support future research on engineering doctoral identity formation.

Background

Research related to identity development in engineering students has primarily focused on undergraduate students[4,5,6,7]. Meanwhile, graduate students appear to differ meaningfully from undergraduate students in a number of ways that could impact identity formation. For starters, it is common that graduate engineering students have professional work experience (either full-time or through co-ops and internships) at the time of their enrollment in the graduate program, while this prior professional experience is much less common for undergraduate students. In the case of doctoral studies in particular, researchers thus often have the assumption that students enter their programs with a defined professional identity as engineers (i.e., an intact "engineering identity"). However, this professional identity needs to be extended in doctoral programs to establish an identity unique to doctoral education as an engineering researcher. Thus, a key focus becomes how the doctoral program can best support and guide the student in the formation of this research identity[8,9].

Current literature regarding different aspects of identity and how to measure them is diverse, from the ethnic identity scale to measure ethnic identity[10], to the U-MICS scale to measure the parental identity domain[11]. Godwin and Kirn define one aspect of professional identity, engineering role identity or simply "engineering identity", as "how students describe themselves and are positioned by others in the role of being an engineer"[12]. Godwin developed a set of items to assess three underlying constructs of engineering identity: recognition (R), interest (I), and competence or performance (C)[1]. Godwin based her work on the existing physics, math, and science identity scales, which had been extensively validated in previous work[13,14,15,16,17,18] Perkins et al. (2018)[2] subsequently used Godwin's engineering identity scales as a starting point for the generation of scales used to measure different aspects of professional identity in graduate engineering students (they developed scales to measure engineering, scientist, and researcher identity, respectively). However, they significantly expanded Godwin's original scales by generating and testing several new items based on data gathered through interviews with engineering doctoral students. For comparison, Godwin's original engineering identity scales contain 11 total items. Perkin et al.'s researcher identity scales, which aim to measure the same constructs as in the current research, originally contained 26 total items, but were reduced 16 total items following the factor analyses of these scales and those of the related identities (scientist and engineering). One unique advantage of Perkin et al.'s approach is that many of the items provided a more detailed reflection on the specific context of doctoral education. For example, the dissertation advisor is proposed as a critical external source of recognition and thus the following item was added: "My advisor(s) see me as a RESEARCHER."[2] Similarly, the competence scale in Perkins et al. work focuses more on specific competencies associated with research, such as delivering research presentations and analyzing and interpreting data, compared with the more general professional competencies baselined in an undergraduate population developed by Godwin. The potential tradeoff of Perkin's approach is in parsimony, specifically in the recognition (six items vs. Godwin's three) and interest (five items vs. Godwin's three) scales, as the competence scale is the same length as in Godwin's measure. However, it is noted that concern for parsimony was a significant driver in Perkin et al.'s reduction of the total instrument length from 26 items to 16 items, and even these two expanded scales would not be considered overly long by most survey scale design guidelines.[19]

The current study understands the research identity role for engineering graduate students as the ways students describe themselves and are positioned by others in the role of being a researcher. This definition is important, particularly if we consider that research has proven that having a structure for identity formation, which includes explicitly considering the development process, is both a necessary element in practice and a gap in the current literature.[20] One purpose of this work is to compare the overall scale lengths, and, where possible the reliabilities of the current scales, of the adapted scales in this research to those published in previous work on related constructs discussed above. The next section describes the survey adaptation, the initial validation results, comparisons to related measures, and the study conclusions and future work, respectively.

Survey Adaptation

The adapted survey scales, the process of creating them, and some initial reliability data using a smaller preliminary sample were first presented in a 2023 Institute of Industrial and Systems Engineers (IISE) Annual Conference paper[21]. The current paper contains additional details on the scale development, more extensive validation data using a larger sample than previously, as well as comparisons to other related measures. Table 1 below compares Godwin's engineering identity items[1] with the research identity items adapted for this work, as well as Perkin et al.'s related measure. [2] The items are presented in Table 1 based on the relative order in which they appear in the current survey, and, where possible, the most similar items in Godwin's engineering identity measure and Perkin et al.'s researcher identity measure are placed adjacent to the current scale items to facilitate content comparisons.

As previously discussed in the current paper, the items developed by Godwin to measure engineering identity hypothesize that identity is represented through three different constructs.[1] As Godwin's measure is a psychometric measure, all items intend to capture the self-perceptions of the participant (respondent) regarding these constructs. First, the recognition construct aims to measure the extent to which important others (parents, instructors, and peers) view the respondent as an engineer. The interest construct focuses on the enjoyment, fulfillment, and other aspects of self-perceived interest in doing engineering work. Finally, the competence construct centers on confidence levels, self-perceived preparedness, and experience in which others ask for help regarding engineering knowledge and work.

This study adopted a close adaptation of Godwin's engineering identity scales[1] to measure research identity, aiming at minimizing wording changes. In this study's adaptation of items, the same constructs of recognition, interest, and competence were used. Recognition now aims to measure to what extent peers, instructors, and family view the respondent as a researcher. Interest now focuses on the self-perceived fulfillment, enjoyment, and other indicators of interest that respondents had while doing research. Competence now centers on understanding, positive feedback from experiences, confidence levels, and experiences where others ask for help regarding research projects and work. To avoid potential order effects, the order of the items in the actual survey was randomized such that recognition, interest, and competence items are interspersed with one another rather than occurring sequentially. However, the items are grouped together in Table 1 below for greater clarity.

As discussed above, the complementary work of Perkins et al.[2] used a different approach to adapting Godwin's scales,[1] including the generation and testing of several new items. It is noted that, following the process of independently adapting Godwin's survey in the current work, two of the three recognition items (the first and third items in Table 1) were observed to use identical wording to items in Perkins et al. (It should be further noted that the question about family recognition was initially included but ultimately removed by Perkins et al. in the final construction of their scales). This small degree of overlap is not surprising as both Perkins et al. and the current study aimed at adapting Godwin's model, using different approaches. Even though Perkins et al. was not used directly for the development of the scales in this study, but rather for comparison after the fact, Perkins et al. is noted both here and in the IISE conference paper[21] as the source for the two identical items as they first proposed this specific wording. The rest of the items in these complementary research identity scales were non-identical, with some relatively similar and others quite distinct.

Construct	Engineering Identity[1]	Research Identity[21]	Researcher Identity[2]
Recognition	My peers see me as an engineer	My peers see me as a researcher.[2]	My peers see me as a RESEARCHER
	My instructors see me as an engineer	My instructors in my current degree program see me as a researcher.	My department faculty see me as a RESEARCHER
	My parents see me as an engineer	My family sees me as a researcher.[2]	My advisor(s) see me as a RESEARCHER
			I have had experiences in which I was recognized as a RESEARCHER
			I see myself as a RESEARCHER
			Other researchers see me as a RESEARCHER
Interest	I find fulfillment in doing engineering	I find fulfillment in doing research.	I find satisfaction when doing RESEARCH
	I enjoy learning about engineering	I enjoy learning how to do research.	I enjoy conducting RESEARCH
	I am interested in learning more about engineering	I am interested in learning more about research.	I am interested in learning more about how to do RESEARCH
			I find satisfaction when learning about my RESEARCH topic
			I want to be recognized for my contributions to RESEARCH
Performance/Competence	I understand concepts I have studied in engineering	I understand the research concepts I have studied in my current PhD degree program.	I understand the concepts needed to analyze and interpret data
	I can do well on exams in engineering	I can do well on research projects in my current field of study.	I can publish research results in my field
	I am confident that I can understand engineering in class	I am confident that I can understand the research concepts presented in my classes in my current degree program.	I am confident that I can design a RESEARCH study
	Others ask me for help in this subject	Others ask me for help using research concepts.	I can present research related topics to relevant audiences
	I am confident that I can understand engineering outside of class	I am confident that I can apply research concepts outside of class.	I am confident that I can network with other researchers

Table 1: Godwin’s (2016) items and Perkin’s et al. (2018) items compared with the current items.

Initial Validation of Adapted Survey

To initially validate the adapted survey, the survey was distributed online (via email link and QR code) at a large research university in the United States during 2023, and then analyzed using exploratory factor analysis and Cronbach's alpha. The survey data collection was conducted in two waves. First, data were collected in Spring 2023 from a cohort of doctoral students within the Industrial, Manufacturing, and Systems Engineering (IMSE) department who were the focus of the larger study. Next, data were collected in Summer 2023 from doctoral students pursuing other majors in the college, including electrical, mechanical, civil, chemical, and petroleum engineering, and computer science. Participants were from both on-campus and off-campus degree programs, and both part-time and full-time students were included.

The survey had a total of 35 student participants who sufficiently completed the research identity items in the survey. However, the initial response to the survey was noticeably higher, with an additional 14 non-IMSE students beginning the survey but not completing the items that are the focus of this research. Meanwhile, there were no IMSE students that provided such type of response. While data indicates that the survey took, on average, around 10-15 minutes to complete, there were a total of 100 items in the survey, and the research identity items occurred at the end of the survey and thus were more prone to attrition. As of Fall 2022, there were 442 doctoral students enrolled in the college; this yields an approximate response rate of 7.9% in terms of usable surveys and 11.1% overall, both of which fall in the typical range for online surveys (6-15%).[22] Demographics show 22 men (63% of the total), 13 women (37% of the total), and none in other gender categories. Of these participants, 22 had not yet completed their qualifying exam for candidacy, nine were doctoral candidates without their proposal submitted, three were in the process of finishing their dissertation for their final defense, and only one had finished the final defense. In race/ethnicity terms the participants defined themselves as White (13), Asian (10), Black (4), Latinx or Hispanic (3), Middle Eastern (3), and another race or ethnicity (2).

It is noted that the overall sample size of 35 is relatively small, even for the small total number of items in the research identity constructs (11 total). Although there are no "hard-and-fast" rules for minimum sample sizes[23,24], many sources suggest a respondent-item ratio of 5:1[25,26] or even 10:1.[27] Others focus on achieving a certain minimum overall sample size, such as 50,[24] 100-150, [26,28] and 200 responses.[29,30] Based on analysis of existing recommendations, the original minimum target for the response was 55 participants. Yet, even after two rounds of follow-up, this minimum response was not achieved. However, the 35 participants do exceed other suggested minimum thresholds, such as 2:1 respondents-to-items, which Kline (1994)[31] suggests can be acceptable in some contexts. Further, the examination of the empirical measures of fit, as discussed below, overall, suggests the sample size is adequate. Still, it will be beneficial in future research to collect additional data to further validate the initial model.

This study used IBM SPSS as the software to analyze responses from participants on the adapted survey. Multiple methodologies within the framework of exploratory factor analysis (principal components extraction with oblimin rotation) were used to assess the validity of the instrument. One technique is the correlation matrix, which is used to evaluate the degree of relationship between items.[32] Another technique used is the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy, which indicates the proportion of variance in the data that might be caused by underlying factors.[33] The KMO test helps to indicate how useful a factor analysis is for the data. Meanwhile, Barlett's test of sphericity was used to test the hypothesis that the correlation matrix is an identity matrix, which would indicate that items are unrelated and thus, unsuitable for structure detection through factor analysis.[33] A pattern matrix shows the unique contribution of a variable to a factor.[34] Finally, the component correlation matrix technique presents the correlation between the extracted factors to confirm which type of rotation, orthogonal or oblique, should be used.[35]

Table 2 shows the correlation matrix between adapted items. The code for each item includes a final subindex with the construct that is assessed. In this case, "R" is for Recognition, "I" for Identity, and "C" for Competence. As the table shows, as expected, correlations are higher between items assessing the same constructs. This shows consistency among the entire correlation matrix of items. Examining the determinant also helps evaluate whether adjustments are beneficial. Usually, adjustments should be considered when the determinant is higher than 0.00001. Since the determinant of this matrix is 0.001, which is greater than 0.00001, this indicates there is a need to check the correlation matrix for high "unexpected correlations" (i.e., strong correlations between items purported to measure different constructs). However, all unexpected correlations are in the weak or low-medium correlation range,[36] and none of these unexpected correlations are equal to or higher than the correlations between items assessing the same construct, suggesting a lack of support for adjustments in this case.

Correlation Matrix[a]

		Q23-25_1_R	Q23-25_2_I	Q23-25_3_R	Q23-25_4_I	Q23-25_5_C	Q23-25_6_I	Q23-25_7_C	Q23-25_8_C	Q23-25_9_R	Q23-25_10_C	Q23-25_11_C
Correlation	Q23-25_1_R	1.000	.101	.517	.168	.404	.345	.266	.419	.598	.406	.238
	Q23-25_2_I	.101	1.000	.472	.561	.379	.586	.247	.209	.269	.163	.219
	Q23-25_3_R	.517	.472	1.000	.516	.412	.331	.331	.358	.651	.440	.404
	Q23-25_4_I	.168	.561	.516	1.000	.554	.539	.539	.447	.580	.422	.473
	Q23-25_5_C	.404	.379	.412	.554	1.000	.512	.616	.461	.510	.695	.739
	Q23-25_6_I	.345	.586	.331	.539	.512	1.000	.476	.496	.326	.307	.360
	Q23-25_7_C	.266	.247	.331	.539	.616	.476	1.000	.601	.601	.528	.586
	Q23-25_8_C	.419	.209	.358	.447	.461	.496	.601	1.000	.386	.529	.481
	Q23-25_9_R	.598	.269	.651	.580	.510	.326	.601	.386	1.000	.622	.507
	Q23-25_10_C	.406	.163	.440	.422	.695	.307	.528	.529	.622	1.000	.671
	Q23-25_11_C	.238	.219	.404	.473	.739	.360	.586	.481	.507	.671	1.000
Sig. (1-tailed)	Q23-25_1_R		.287	.001	.175	.010	.025	.067	.008	<.001	.010	.091
	Q23-25_2_I	.287		.003	.000	.015	.000	.083	.122	.065	.182	.110
	Q23-25_3_R	.001	.003		.001	.009	.030	.030	.021	.000	.005	.010
	Q23-25_4_I	.175	.000	.001		.000	.001	.001	.005	.000	.007	.003
	Q23-25_5_C	.010	.015	.009	.000		.001	.000	.003	.001	.000	.000
	Q23-25_6_I	.025	.000	.030	.001	.001		.003	.002	.032	.041	.020
	Q23-25_7_C	.067	.083	.030	.001	.000	.003		.000	.000	.001	.000
	Q23-25_8_C	.008	.122	.021	.005	.003	.002	.000		.013	.001	.002
	Q23-25_9_R	.000	.065	.000	.000	.001	.032	.000	.013		.000	.001
	Q23-25_10_C	.010	.182	.005	.007	.000	.041	.001	.001	.000		.000
	Q23-25_11_C	.091	.110	.010	.003	.000	.020	.000	.002	.001	.000	

a. Determinant = .001

Table 2: Correlation matrix of items in the survey.

As previously indicated, the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) is a statistic that indicates the proportion of variance in the data set that might be caused by the underlying factors.[33] The results of a factor analysis can be suspect if KMO is lower than 0.5. As shown in Table 3, the current survey has a KMO value of 0.714; thus, it can be assumed that the factor analysis results are useful for understanding the variation in the data set.[33] Bartlett's test of sphericity examines the hypothesis that the correlation matrix is an identity matrix. This would indicate that the variables analyzed are unrelated and therefore unsuitable for structure detection through factor analysis.[33] Significance levels (p-values) under 0.05 for Bartlett's test show a high level of confidence that factor analysis can be useful in evaluating the underlying structure of the data, which is this case for the current data set as shown in Table 3 ($p < .001$).

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.714
Bartlett's Test of Sphericity	Approx. Chi-Square	199.778
	df	55
	Sig.	<.001

Table 3: Kaiser-Meyer-Olkin test and Bartlett's Test computed from IMB SPSS.

Finally, the component correlation matrix presents the correlation between the extracted components.[35] As Table 4 shows, the inter-correlation of each component (correlations between components 2 and 3, as well as between 1 and 3, and between 1 and 2) are weak correlations. This indicates that the factor analysis, used with principal components extraction and oblique rotation, is a good fit for analyzing the data.

Component Correlation Matrix

Component	1	2	3
1	1.000	.378	.468
2	.378	1.000	.268
3	.468	.268	1.000

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

Table 4: Component correlation matrix obtained by oblimin rotation with Kaiser normalization.

As the analysis of the correlation matrix, KMO, Bartlett's test, and component correlation matrix, overall, supported the fit of the factor analysis model, the pattern analysis was then analyzed in detail to assess the extent to which the items loaded on the intended constructs. A pattern matrix is a matrix containing the coefficients for the linear combination of the variables.[37] There are two general families of rotations possible, orthogonal (when it is assumed that the factors are uncorrelated) and oblique (when factors are allowed to be correlated).[38] The values obtained in the pattern matrix are the regression coefficients expressed as a function of the factors. As Table 5 shows, component 1 represents the Competence construct, component 2 represents the Identity construct, and component 3 represents the Recognition construct. All factor loading are high on the intended construct (greater than 0.4) and much less on the other dimensions (less than 0.4).

Pattern Matrix[a]

	Component		
	1	2	3
Q23-25_1_R	.002	-.128	.908
Q23-25_2_I	-.139	.951	.058
Q23-25_3_R	-.057	.335	.752
Q23-25_4_I	.363	.612	.048
Q23-25_5_C	.776	.150	.031
Q23-25_6_I	.261	.675	.001
Q23-25_7_C	.814	.102	-.061
Q23-25_8_C	.646	.069	.091
Q23-25_9_R	.326	.039	.662
Q23-25_10_C	.788	-.182	.230
Q23-25_11_C	.904	-.036	-.068

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser

Table 5: Pattern matrix with three components defined using oblimin (oblique) rotation.

The final evaluation of the initial model fit was the assessment of construct reliability through Cronbach's alpha. This showed values of 0.816 for Recognition, 0.794 for Interest, and 0.866 for Competence. In general terms, a Cronbach's alpha of 0.7 and above is good, but 0.8 and above is preferred.[39] Thus, all constructs show strong reliability with two constructs having reliabilities greater than 0.8 and the third very close to 0.8.

Comparison to Other Measures of Related Constructs

Table 7 includes a comparison between the construct reliabilities (Cronbach's alpha values) observed in this research and those observed in the 2023 IISE conference paper by the same authors[21] (which used identical measures but a smaller data set from 2022), and the related measures of Godwin[1], Perkins et al.[2], and Godwin et al.[18,19] It is noted that the 2023 IISE conference paper only included data from an earlier (2022) survey of the IMSE cohort (n = 12), whereas the current paper contains data from both IMSE and non-IMSE doctoral students (n=35). Further, due to its sample size, the IISE 2023 conference paper did not attempt factor analysis.

The only two families of scales that aim to measure research identity are those developed in this research and the 2023 IISE paper,[21] and in the complementary work by Perkins et al.[2] However, as noted in Table 7 below, Cronbach alpha values were not provided in the latter work. Thus, the

Perkins et al. scale is included in Table 7 solely for the comparison of relative parsimony (in terms of total number of items) of the scales.

Godwin's engineering identity measure[1] is also offered for comparison. In addition, although several studies could be used for comparison of the math, science, and physics identity scales, the selected comparisons are Godwin et al. (2013)[18] and Godwin et al. (2016).[19] This is due to the desire to most closely align the comparisons to the latest iteration of the work that Godwin used to develop the engineering identity measure.

Several observations can be made based on Table 7. First, in considering the various recognition scales for the different aspects of identity, most were reliable (i.e., Cronbach's alpha $\geq$ 0.70), except for the science identity recognition scale from Godwin et al. (2013).[18] This scale used wording that was quite different from the other measures being compared (e.g., incomplete sentences) and focused only on recognition by the family of origin versus other parties. The other Cronbach's alpha values ranged from 0.77 (Godwin, 2016[1]) to 0.93 (the IISE 2023 paper[2]). However, as the IISE conference paper sample size was very small, the Godwin mathematics identity recognition scales[19] likely form a more stable upper bound for the current comparison, at 0.88. With a Cronbach's alpha value of 0.82, the current research identity recognition scales fall in the middle of the comparison group and are nearly identical to that of the Physics identity recognition scale in Godwin et al. (2016).

In terms of interest, all the compared scales are reliable, with a Cronbach's alpha range of 0.79 (both the current study and the 2023 IISE conference paper[21]) to 0.90 (Godwin et al., 2016,[19] mathematics identity). It is observed that the current research identity interest scale represents the low end of this range, although it is still reasonably close to the next highest reliability (0.85 for Godwin et al., 2013).

Finally, in terms of competence, all scales are again reliable, with Cronbach's alpha values ranging from 0.78 (the 2023 IISE conference paper[21]) to 0.94 (Godwin et al., 2016,[19] physics and mathematics identity). In this comparison, the current scale reliability (0.87) is nearly identical to that of Godwin's corresponding engineering identity scale[1] (0.88).

In terms of overall parsimony, the research identity scales in the current research (and the 2023 IISE conference paper,[21] which used the same scales) contained 11 total items, as did Godwin's engineering identity measure.[1] The physics and mathematics identity scales[19] were similar length, each containing 10 total items. Meanwhile, the research identity scale developed by Perkins et al.[2] and the science identity scale[18] were a bit (approximately 50%) longer, containing 16 total items.

Constructs	Current survey – Research identity (n=35)	IISE 2023 conference paper[21] – Research identity (n=12)	Perkins et al.[2] – Researcher identity (n=107)	Godwin[1] – Engineering identity (n=371)	Godwin et al.[19] – Physics identity (n=6,772)	Godwin et al.[19]– Math identity (n=6,772)	Godwin et al.[18] – Science identity (n=6,772)
Recognition	0.82 (3 items)	0.93 (3 items)	Not reported (6 items)	0.77 (3 items)	0.83 (2 items)	0.88 (2 items)	0.41 (4 items)
Interest	0.79 (3 items)	0.79 (3 items)	Not reported (5 items)	0.89 (3 items)	0.89 (2 items)	0.90 (2 items)	0.85 (5 items)
Competence	0.87 (5 items)	0.78 (5 items)	Not reported (5 items)	0.88 (5 items)	0.94 (6 items)	0.94 (6 items)	0.90 (7 items)
Total Items	11	11	16	11	10	10	16

Table 7: Comparison between reliabilities for current survey and related measures.

Conclusions and Future Work

This study has adapted items from the survey developed by Godwin at the 2016 ASEE conference to measure engineering identity[1]. Using the same three constructs she proposed, this study implements and tests minor changes in the specific wording of the items in order to measure research identity in engineering doctoral students. Results from this study provide preliminary support that the adaptation of the items provide a valid and reliable measure of research identity in doctoral students. The holistic consideration of the fit statistics from the exploratory factor analysis suggests an adequate model fit, providing initial evidence for the construct validity of the model, with only correlation matrix determinant suggesting that further modifications may be beneficial; however, a more detailed analysis of the correlation pattern did not support this conclusion. Furthermore, the Cronbach's alpha values on all constructs were greater than 0.7 and all but one were greater than 0.8, indicating adequate reliability.[39] Finally, comparisons with other related constructs indicated that the construct reliabilities in the current study were overall similar to those of the most closely related constructs in previous work, and the length of the scale was identical or nearly identical to several of the measures and noticeably shorter than others.

As with all research, study limitations should be noted. The first discussed here is that the sample size in this study was smaller than originally targeted and lower than the typical sample size for exploratory factor analysis, even though the empirical fit measures suggest that the model is adequate. It will therefore be important to continue to collect data in future research to further validate the model. In addition, future work should also investigate whether the scales used for this research demonstrate any changes in validity and reliability when considering different demographic groups (e.g., different ethnoracial groups), as such subgroup analysis could not be conducted given the current sample size. Further, the current data set only included one measurement per participant; thus, validity and reliability were not assessed in the context of a data set that included repeated measurements on the same participant over time. Second, this study only directly assessed construct validity, which is only one aspect of measurement validity. Face validity and content validity are primarily addressed through use of existing related scales (i.e., the adaptation of Godwin's scales[1]). However, future research can also consider whether cognitive interviewing would be useful to further evaluate the content validity of the scales. In addition, this study did not attempt to assess concurrent or predictive validity, which could be considered in future research. In particular, it would be very interesting to compare the concurrent validity and reliability of the scales in the current research to those in the longer scale designed by Perkins et al (2018),[2] as the latter offers an expanded conceptualization of researcher identity, with several items focused on detailed aspects of this role identity in the context of doctoral education, which could support enhanced content validity. By definition, all scales attempting to measure latent variables require a sampling of items – it is impossible to represent all aspects of a construct – however, there is a trade-off between parsimony (which can reduce survey fatigue) and promote response, and the potential for enhanced content (and at times other aspects of) validity due to using a longer scale.[19]

Other future work includes the longitudinal study of research identity formation utilizing the survey constructs in this paper as well as other data sources. Efforts will be made to analyze how a researcher's identity changes over time individually or aggregately, and what factors influence this process. Further, in the current study, multiple engineering disciplines were included, but all of these were in the same university. Thus, future work could also use the survey to study research identity in doctoral students from other university contexts. Moreover, this measurement instrument focused on research identity only, based on the prevailing belief that most universities expect doctoral students to have a professional identity when they enroll and thus focus primarily on forming their research identity. However, future work should further test this assumption (e.g., finding if/how significant change in other aspects of professional identity might also occur during doctoral education), and could also include the study of research identity in industrial and faculty contexts to analyze how research identity impacts effectiveness and other longitudinal professional success measures.

Acknowledgment

This material is based upon work supported by the National Science Foundation under Award No. (No. 2205033). Any opinions, findings conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

References

1. Godwin, A., 2016, "The Development of a Measure of Engineering Identity," In ASEE Annual Conference & Exposition. June 2016. https://peer.asee.org/26122
2. Perkins, H., Bahnson, M., Cass, C., Tsugawa-Nieves, M., Kirn, A., 2018, "Development and testing of an instrument to understand engineering doctoral students' identities and motivations." In 2018 ASEE Annual Conference & Exposition. June 2018. https://peer.asee.org/30319
3. Nunnally, B., Farkas, D., 2016, UX research: practical techniques for designing better products. Boston: O'Reilly Media, Inc.
4. Choe, N., Borrego, M., 2019, "Prediction of engineering identity in engineering graduate students". IEEE Transactions on Education, Vol. 62 No. 3, pp. 181-187. https://ieeexplore.ieee.org/abstract/document/8667045
5. Bahnson, M., Perkins, H., Tsugawa, M., Satterfield, D., Parker, M., Cass, C., and Kirn, A., 2021, "Inequity in graduate engineering identity: Disciplinary differences and opportunity structures". Journal of Engineering Education, Vol. 110 No. 4, pp. 949-976. https://onlinelibrary.wiley.com/doi/abs/10.1002/jee.20427
6. Morelock, J., 2017, "A systematic literature review of engineering identity: definitions, factors, and interventions affecting development, and means of measurement". European Journal of Engineering Education, Vol. 42 No. 6, pp. 1240-1262. https://doi.org/10.1080/03043797.2017.1287664
7. Elizondo-Noriega, A., Tiruvengadam, N., Cargile-Cook, K., Cross, J., Beruvides, M., 2020, "Understanding Engineering Identity Formation Mechanisms in Graduate and Undergraduate Education: A State-of-the-Art Matrix Analysis". In *IIE Annual Conference. Proceedings,* pp. 1-6. Institute of Industrial and Systems Engineers (IISE). May 2020. https://www.proquest.com/docview/2522431819
8. Caskey, M., Stevens, D., Yeo, M., 2020, "Examining doctoral student development of a researcher identity: Using the draw a researcher test". Impacting Education: Journal on Transforming Professional Practice, Vol. 5 No. 1. Available: https://doi.org/10.5195/ie.2020.92
9. Hall, L, Burns. L., 2009, "Identity development and mentoring in doctoral education," Harvard Educational Review, Vol. 79 No. 1, pp. 49-70. https://meridian.allenpress.com/her/article-abstract/79/1/49/31955/Identity-Development-and-Mentoring-in-Doctoral
10. Yoon, E., 2011, "Measuring Ethnic Identity in the Ethnic Identity Scale and the Multigroup Ethnic Identity Measure-Revised," Cultural Diversity and Ethnic Minority Psychology, Vol. 17 No. 2, pp. 144–155. https://doi.org/10.1037/a0023361
11. Piotrowski, K., 2018, "Adaptation of the Utrecht-Management of Identity Commitments Scale (U-MICS) to the measurement of the parental identity domain," Scandinavian Journal of Psychology, Vol. 59 No. 2, pp. 157–166. https://doi.org/10.1111/sjop.12416

12. Godwin, A., Kirn, A., 2020, “Identity-based motivation: Connections between first-year students’ engineering role identities and future-time perspectives,” Journal of Engineering Education, Vol. 109 No. 3, pp. 362–383. https://doi.org/10.1002/jee.20324
13. Hazari, Z., Sonnert, G., Sadler, P. M., Shanahan, M.-C. C., 2010, “Connecting high school physics experiences, outcome expectations, physics identity, and physics career choice: A gender study,” Journal of Research in Science Teaching, Vol. 47 No. 8, pp. 978–1003. https://doi/pdf/10.1002/tea.20363
14. Cribbs, J. D., Hazari, Z., Sonnert, G.,Sadler, P. M., 2015, “Establishing an explanatory model for mathematics identity,” Child Development, Vol. 86 No. 4, pp. 1048–1062. https://doi/pdf/10.1111/cdev.12363
15. Godwin, A., 2014, Understanding female engineering enrollment: Explaining choice with critical engineering agency (Unpublished doctoral dissertation). Clemson University, Clemson, SC.
16. Godwin, A., Potvin, G., Hazari, Z., 2013, “The development of critical engineering agency, identity, and the impact on engineering career choices,” 2013 ASEE Annual Conference & Exposition, June 2013. https://peer.asee.org/22569
17. Godwin, A., Potvin, G., Hazari, Z., Lock, R., 2013, “Understanding engineering identity through structural equation modeling,” 2013 ASEE/IEEE Frontiers in Education Conference, October 2013. https://doi.org/10.1109/FIE.2013.6684787
18. Godwin, A., Potvin, G., Hazari, Z., Lock, R., 2016, “Identity, critical agency, and engineering: An affective model for predicting engineering as a career choice,” Journal of Engineering Education, Vol. 105 No. 2, pp. 312-340. https://doi/pdf/10.1002/jee.20118
19. Stanton, J. M., Sinar, E. F., Balzer, W. K., Smith, P. C., 2002, “Issues and strategies for reducing the length of self-report scales,” Personnel Psychology, Vol. 55 No.1, pp. 167-194. https://doi/pdf/10.1111/j.1744-6570.2002.tb00108.x
20. van Hoof, A., Raaijmakers, Q. A. W., 2003, “The Search for the Structure of Identity Formation,” Identity, Vol. 3 No. 3, pp. 271–289. https://doi.org/10.1207/s1532706xid0303_06
21. Polanco-Lahoz, D., Carrión-Anampa, F.,L., Cross, J. A., Cook, K. C., Beruvides, M., 2023, “Self-perceptions regarding researcher identity development in engineering doctoral students: Preliminary results,” IIE Annual Conference Proceedings, May 2023, 1-6. https://www.proquest.com/docview/2878501095
22. Manfreda, K. L., Bosnjak, M., Berzelak, J., Haas, I., Vehovar, V., 2008, “Web Surveys versus other Survey Modes: A Meta-Analysis Comparing Response Rates,” International Journal of Market Research, Vol. 50 No.1, pp. 79-104. https://doi.org/10.1177/147078530805000107
23. Osborne, J. W., Costello, A. B., 2009, “Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis,” Pan-Pacific Management Review, Vol. 12 No. 2, pp. 131-146.
24. Iacobucci, D., 2010, “Structural equations modeling: Fit indices, sample size, and advanced topics.” Journal of consumer psychology, Vol. 20 No. 1, pp. 90-98. https://doi/pdfdirect/10.1016/j.jcps.2009.09.003
25. Bollen, K. A., 1989, Structural models with latent variables. New York, NY: Wiley.
26. Hatcher, L., 1994, A step-by-step approach to using the SAS system for factor analysis and structural equation modeling. Cary, NC: SAS Publishing.
27. Tinsley, H.E.A. Tinsley, D.J., 1987, “Uses of factor analysis in counseling psychology research,” Journal of Counseling Psychology, Vol. 34 No. 4, pp. 414-424. https://doi.org/10.1037/0022-0167.34.4.414
28. Anderson, J., Gerbing, C., 1984, “The effect of sampling error on convergence, improper solutions, and goodness-of-fit indices for maximum likelihood confirmatory factor analysis,” Psychometrika, Vol. 49 No. 2, pp. 155-173. https://doi.org/10.1007/BF02294170
29. Curran, P., Boleyn, K. A., Chen, F., Paxton, P., Kirby, J. B., 2003, “Finite sampling properties of the point estimates and confidence intervals of the RMSEA,” Sociological Methods and Research, Vol. 32, pp. 208-252. https://doi.org/10.1177/0049124103256130
30. Herzog, W., Boomsma, A., 2009, “Small-sample robust estimators of noncentrality-based and incremental model fit,” Structural Equation Modeling, Vol. 16, pp. 1-17. https://doi.org/10.1080/10705510802561279
31. Kline, P., 1994, An Easy Guide to Factor Analysis, London: Routledge.
32. ScienceDirect, 2024, Correlation Matrix. https://www.sciencedirect.com/topics/mathematics/correlation-matrix
33. IBM SPSS documentation editors, 2021, KMO and Barlett’s test. https://www.ibm.com/docs/en/spss-statistics/28.0.0?topic=detection-kmo-bartletts-test
34. USQ pressbooks editors, 2024, Section 8.5: EFA Interpretation. https://usq.pressbooks.pub/statisticsforresearchstudents/chapter/efa-

interpretation/#:~:text=Pattern%20Matrix%20%26%20Structure%2FFactor%20Matrix&text=The%20pattern%20matrix%20shows%20the,is%20more%20complicated%20to%20interpret.

35. Kooststra, G. J., 2004, Exploratory Factor Analysis Theory and Application.
36. IBM SPSS documentation editors, 2022. Correlation Settings (published February 14, 2022). https://www.ibm.com/docs/en/spss-modeler/18.3.0?topic=tab-correlation-settings
37. Factor Analysis | SPSS Annotated Output. UCLA: Statistical Consulting Group, 2024, https://stats.oarc.ucla.edu/spss/output/factor-analysis/#:~:text=The%20factor%20structure%20matrix%20represents,linear%20combination%20of%20the%20variables (accessed January 31, 2024).
38. IBM Support Editors, 2020, IBM Support - Pattern Matrix and Structure Matrix Definition in SPSS FACTOR output (published April 16, 2020). https://www.ibm.com/support/pages/pattern-matrix-and-structure-matrix-definition-spss-factor-output
39. Nunnally, J., Bernstein, I., 1994, Psychometric Theory (3rd Edition) (Third Edition). McGraw Hill series in Psychology.