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Exploring the Validity of the Engineering Design Self-Efficacy Scale for Secondary School Students (Research To Practice)

Dr. Eunsil Lee, Florida International University

Eunsil Lee is a postdoctoral associate at Florida International University in the School of Universal Computing, Construction, and Engineering Education. She received a B.S. and M.S. in Clothing and Textiles from Yonsei University (South Korea) with the concentration area of Nanomaterials and Biomaterials in Textiles. She began her Ph.D. study in Textile Engineering but shifted her path toward Engineering Education, earning her Ph.D. in Engineering Education from Arizona State University. Her research interests center on inclusion in engineering with focuses on students' sense of belonging, faculty and peer interactions, diversity in citizenship, and engineering doctoral education. Prior to her Ph.D., She worked as a research associate at the Korean Institute of Science and Technology, Carbon Composite Materials Research Center.

Dr. Adam R. Carberry, Arizona State University

Dr. Adam Carberry is an associate professor at Arizona State University in the Fulton Schools of Engineering, The Polytechnic School. He earned a B.S. in Materials Science Engineering from Alfred University, and received his M.S. and Ph.D., both from Tufts University, in Chemistry and Engineering Education respectively. His research investigates the development of new classroom innovations, assessment techniques, and identifying new ways to empirically understand how engineering students and educators learn. He currently serves as the Graduate Program Chair for the Engineering Education Systems and Design Ph.D. program. He is also the immediate past chair of the Research in Engineering Education Network (REEN) and an associate editor for the Journal of Engineering Education (JEE). Prior to joining ASU he was a graduate student research assistant at the Tufts' Center for Engineering Education and Outreach.

Dr. Medha Dalal, Arizona State University

Medha Dalal is a postdoctoral scholar in the Fulton Schools of Engineering at Arizona State University. She received her Ph. D. in Learning, Literacies, and Technologies with an emphasis on engineering education from the Arizona State University. Her research seeks to build capacity for engineering education stakeholders at the grassroots, while also informing policy. Three thrusts that define her research interests at the intersections of engineering, technologies, and education include, ways of thinking that address complex educational challenges, democratization of K-12 engineering education, and online and technology-based learning.

Matthew J. Miller PhD, Loyola University Chicago

Matthew J. Miller received his Ph.D. in counseling psychology from Loyola University Chicago and is currently holds the Walter P. Krolikowski, SJ Endowed Chair in the School of Education at Loyola University Chicago. He is an Associate Editor of the Journal of Counseling Psychology and his research interests span four related areas: multiculturalism, vocational psychology, social justice engagement, and applied psychological measurement.

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Introduction and Background

Pre-college engineering education efforts and associated research has seen a sharp rise in the last two decades to address the growing needs of providing engineering experiences at the elementary and secondary levels [1-2]. The existing literature has expanded our understanding of pre-college engineering curricula, extracurricular activities, teacher professional development efforts, and student motivations. The majority of this work has been conducted as small-scale, exploratory studies [3]. Studies are still needed that explore cognitive and affective constructs within a pre-college engineering context to provide depth of understanding that is reliable and generalizable across different pre-college student populations [4]. The present study aims to partially fill this gap by examining validity evidence associated with the engineering design self-efficacy (EDSE) scale [5] within the context of pre-college engineering education.

Self-efficacy refers to individuals' belief in their capabilities to perform a domain-specific task [6]. According to Bandura's self-efficacy theory [6], self-efficacy plays a significant role in guiding human action and change by having mediating influence on individuals' interest in particular tasks, persistence in the face of obstacles, choice of behavioral activities, and task performance [6]. Bandura hypothesized that self-efficacy within specific domains can be developed by four primary sources of information: (a) performance accomplishment or mastery experiences (i.e., previous successes and failures on similar tasks), (b) verbal or social persuasion (e.g., encouraging or discouraging messages from others), (c) vicarious learning (i.e., observation of social models and self-modeling), and (d) physiological arousal (e.g., enthusiasm or anxiety associated with task performance) [6]. Educational researchers have investigated the sources of self-efficacy in diverse tasks so that such principles can be used in designing instructional strategies [7].

Significant efforts in engineering education have been made to understand the role of self-efficacy for students because of its demonstrated positive impact on student outcomes, such as performance and persistence [8-13]. These studies have investigated and developed measures for different domains of engineering self-efficacy (e.g., general academic, domain-general, and task-specific self-efficacy). The EDSE scale is a frequently cited measure that examines task-specific self-efficacy within the domain of engineering design. This scale has been primarily used by researchers and practitioners with engineering undergraduate students to assess changes in their engineering design self-efficacy as a result of active learning interventions, such as project-based learning [14-16]. Our work has begun to experiment with the use of this scale in a secondary education context. There is a need to examine score validity and reliability of this scale in nonundergraduate populations to better understand the trustworthiness of the measure with other populations (e.g., secondary students).

The following study is situated in the Engineering for US All (e4usa): A National Pilot Program for High School Engineering Course and Database program, a new pre-college engineering initiative funded in 2018 by the National Science Foundation. The program aims to demystify engineering for all high school students as an avenue to engineering literacy and a means of enhancing potential engineering pathways [17]. The e4usa course was intentionally designed to be inclusive by providing engineering design experiences relating to student fields of interest in local and global contexts. The course objectives are broken down into four major threads and woven through seven units. The four threads include: a) discovery of the discipline of engineering and engineering identity, b) intersection of society and engineering, c) professional skills of teaming, communication, and project management, and d) process of engineering design. The year-long course was designed based on the First Year Engineering Classification Scheme, which was used to classify all possible content found in first-year Introduction to Engineering courses in general-admit engineering programs [18]. The intent was not only to create a bridge course for students who may want to select engineering majors in universities, but also to develop engineering-centric skills (e.g., problem-solving, design thinking, innovation, evaluation, and iteration) that cut across a broad range of fields and prepare students for 21st century careers.

The e4usa course was piloted in nine high schools across the United States during the 2019 - 2020 academic year. The void of validity and reliability evidence reported for this scale among the pre-college student population prompted the research team to examine the instrument's score validity and reliability to support proper use of the EDSE scale for researchers and practitioners in pre-college engineering education settings. The following subsections describe and discuss the methods used, emergent results, conclusions, and future potential directions.

Methods

Measure

Data used for this study is part of a dataset collected to evaluate student outcomes from the implementation of e4usa curriculum. The measured student outcomes include the changes in students' beliefs and attitudes towards their ability to perform engineering design and engineering as a future career pathway. A pre and post-survey design was used for the larger study to compare the students' responses before and after the course; the current study only used the data from the post-survey. The data were collected using a survey developed by the e4usa research team consisting of researchers in engineering education, psychology, and traditional engineering disciplines. The complete survey contains 56 items broken down into three sections, including six demographic items.

Student self-efficacy to conduct engineering design activities was examined using the EDSE scale [5]. The scale prompts participants to rate their degree of confidence, i.e., self-efficacy, to perform engineering design tasks using an 11 point generic scale from 0 (low confidence) to 10 (high confidence) (see Table 1). The original first item - conduct engineering design - of the scale was removed for this study. This item was designed to capture engineering design using a single item. We chose to focus on capturing student perceptions of engineering design by presenting embedded steps rather than a single item.

Table 1 Engineering Design Self-Efficacy (EDSE) Scale

<table>
<tr><td colspan="2">Instruction: In this section, please rate your degree of confidence to perform the following tasks.</td></tr>
<tr><th>Item</th><th>Scale</th></tr>
<tr><td>Identify a design need</td><td rowspan="8">Please use the following scale:

0 = low confidence
5 = moderate confidence
10 = high confidence

Example:
0 1 2 3 4 5 6 7 8 9 10
low ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ high</td></tr>
<tr><td>Research a design need</td></tr>
<tr><td>Develop design solutions</td></tr>
<tr><td>Select the best possible design</td></tr>
<tr><td>Construct a prototype</td></tr>
<tr><td>Evaluate and test a design</td></tr>
<tr><td>Communicate a design</td></tr>
<tr><td>Redesign</td></tr>
</table>

This scale was originally designed with the intent of measuring undergraduate engineering students' self-efficacy toward engineering design. Initial work conducted by Carberry et al. [5] using a diverse sample of individuals - engineering or engineering education professors, engineers, engineering education graduate students, engineering graduate students, engineering undergraduate students, non-engineers with science backgrounds, and non-engineers without science backgrounds - revealed a single factor among the eight items plus three separate factors around motivation, expectancy for success, and anxiety. Replication work later conducted by Major et al. [19] using a sample of undergraduate engineering students revealed a potential overlap between confidence and expectancy for success following CFA. Evidence of score validity and reliability provided through these two studies, along with various additional uses of the instrument (e.g., [20-22]), support the structure and reliability of the instrument.

Procedure

Data for the current study were collected over two weeks in Spring 2020 with students enrolled in the e4usa course. The e4usa teachers solicited students' participation in the online survey by first collecting student assent and parental consent forms. Teachers sent a follow-up recruitment email to students to participate in the online survey using a Google Form. Responses from the students who submitted both assent and consent forms were used among all the responses collected. Students' responses were collected from six schools located in different regions across the US.

Participants and Demographics

A total of 151 survey responses were collected; 14 responses were removed on the basis that they did not provide completed responses to the first section for the EDSE scale. The demographics for the final sample of 137 responses is noted in Table 2. The sample was majority female (59%) and self-identified as Black/African American (54%); four participants didn't provide demographic information. The participants' age ranged from 15 to 18 (M = 16 years, SD = 0.83 years).

Table 2. Demographic Information

Gender	
Male	58 (44%)
Female	79 (59%)
Age	
15	38 (28%)
16	74 (54%)
17	15 (11%)
18	10 (7%)
Race / Ethnicity	
American Indian or Alaska native	0 (0%)
Asian	12 (9%)
Black or African American	72 (54%)
Hispanic or LatinX	17 (17%)
Native Hawaiian or Other Pacific Islander	3 (2%)
White	22 (22%)
Multiple races/ethnicities	3 (2%)
International	3 (2%)

Exploratory Factor Analysis

An EFA was conducted for the eight items to explore the number of emergent factors. Factor analysis was conducted using the SPSS statistical software package (v. 25). The assumption that missing data were completely at random (MCAR) was examined by using Little's test [23] prior to EFA analysis. All missing data determined to be MCAR were deleted using listwise deletion because the amount of missing data as a percentage of complete data was only 2%. The final sample includes 137 responses, which met the minimum criterion of at least five to ten respondents per item [24].

Next, the factorability of the EDSE scale was examined using Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity [25]. The KMO test measures the degree of shared variance among items as a function of partial correlations. This means that items having smaller partial correlations result in higher KMO scores as they share a common factor. KMO scores above 0.8 support the existence of an underlying factor(s), indicating that factor analysis is possible. Bartlett's test of sphericity measures the hypothesis that the item correlation matrix is an identity matrix, which represents that factor analysis is not possible as the items are unrelated. A significant test result ($p < 0.05$) rejects the null hypothesis, indicating that the data are factorable [25].

The number of factors were then determined using a scree plot examination, Kaiser test, and parallel analysis [24]. The scree plot is a line plot of eigenvalue factors that shows the point at which extracting more factors does not explain more variance. The Kaiser method retains factors with eigenvalues greater than 1 [24]. Parallel analysis helps determine meaningful factors from a large number of random data sets with the same dimensionality as the real data set for this study. The eigenvalue generated from the random data set is compared with the eigenvalue generated from the real data set. Factors in the real data set with eigenvalues larger than the 95th percentile eigenvalues from its random counterpart are retained. Parallel analysis is regarded as the gold standard to determine the number of factors, but the results from all three methods were considered to determine the number of factors for this study [26].

Factor analysis was conducted using principal axis factoring (PAF), which is recommended for conducting factor analysis in social science research as it allows for the possibility of error (e.g., unique variance) in the measurement of latent constructs [24]. Items with loadings less than 0.4 or cross-loadings on multiple factors greater than 0.3 were removed from the resultant factor structure [27].

Finally, Cronbach's coefficient alpha was used to examine the internal consistency of the resulting factor structure based scale score. A Cronbach's coefficient alpha value serves as a statistical metric of data reliability. Cronbach's alpha values of 0.70 or higher are generally accepted with 0.80 or higher being most desirable in social science research [24].

Results and Discussions

EFA results

The EFA and internal consistency reliability results showed evidence of validity and reliability of the eight item EDSE score. Descriptive statistics (Table 3) demonstrating absolute values of skewness and kurtosis less than 2.0 with inter-item correlations ranging from 0.32 to 0.64 (p=0.00) indicated the appropriateness to perform the EFA analysis using this data. Both the KMO test (score = 0.87) and Bartlett's test (p = 0.000) determined that the item correlation matrix for this scale was factorable. Parallel analysis, Kaiser's criterion method, and the scree plot each suggested a unidimensional factor model; Kaiser's criterion test suggested an eigenvalue of 4.32, explaining 53.98% of the variance accounted for in items by the latent factor.

Table 3. Descriptive Statistics Results

Item number	M	SD	Skew	Kurtosis	Correlation								
					2	3	4	5	6	7	8	9	p
2	7.74	1.64	-0.71	0.29	1.00	0.54	0.44	0.38	0.35	0.46	0.40	0.35	
3	7.69	1.92	-1.12	1.52	0.54	1.00	0.51	0.31	0.36	0.43	0.46	0.54	
4	7.42	1.78	-0.86	1.54	0.44	0.51	1.00	0.55	0.58	0.58	0.48	0.64	
5	7.61	1.64	-0.68	0.41	0.38	0.31	0.55	1.00	0.42	0.39	0.40	0.45	0.00
6	6.96	2.14	-0.93	1.01	0.35	0.36	0.58	0.42	1.00	0.60	0.32	0.61	
7	8.04	1.63	-0.74	-0.15	0.46	0.43	0.58	0.39	0.60	1.00	0.54	0.56	
8	7.61	1.98	-1.18	2.09	0.40	0.46	0.48	0.40	0.32	0.54	1.00	0.53	
9	7.42	1.99	-0.98	1.64	0.35	0.54	0.64	0.45	0.61	0.56	0.53	1.00	

*Note: Response scale ranged from 0 (*low confidence) to *10 (high confidence).*

Table 4 shows the final factor solution with factor loadings and communalities for the eight items in the scale. The final model consisted of all eight items with factor loadings between 0.59 and 0.81. Items two and five showed communalities lower than 0.4, but were not removed from the final factor solution considering the high factor loadings (>0.5). The final factor structure captured the overall process and tasks required to perform the engineering design process. A Cronbach's alpha value of 0.88 revealed a high internal consistency among the items.

Table 4. Exploratory Factor Analysis (EFA) Results

Item	Factor loading	Commonality
Develop design solutions	0.81	0.65
Redesign	0.79	0.62
Evaluate and test a design	0.75	0.56
Construct a prototype	0.68	0.46
Communicate a design	0.65	0.42
Research a design need	0.64	0.41
Select the best possible design	0.59	0.35
Identify a design need	0.59	0.35

Note: 'Item 1. Conduct engineering design' was not included for the EFA analysis.

Table 5. Research settings and participants

		This study	Carberry, 2010
Research settings	Educational context	Secondary education	Higher education
	Course / curriculum implemented	e4usa engineering design curriculum	Learning -through-service (LTS) experience
	Institution	Multi-institution	Single institution
	Survey design	Pre-post survey (Post survey used)	One-time cross-sectional survey
Participants	Number	137	202
	Age (or Year)	15 - 18	21 - 62
	Note	Higher percentage of Black / female participants	Participants with diverse engineering experiences

Descriptive Comparisons of the EFA results

The resultant factor structure and factor loadings of the retained items for this study were compared with findings from a follow-up study conducted by Carberry [20] using a sample of 202 undergraduate engineering students. Comparisons are made here to explore similarities and differences in the factor structures or patterns of factor loadings of the EDSE scale in different educational contexts among varied study populations (see Table 5).

Table 6 presents the factor structure and factor loadings from the two research studies. The factor structure reported by Carberry [28] was replicated in the current study, identifying the same unidimensional factor structure consisting of the same eight items. Adequate EDSE score reliability was found for each study.

Table 6. Comparisons of the EFA results

Item	Factor loading	
	This study	Carberry, 2010
Identify a design need	0.59	0.92
Research a design need	0.64	0.90
Develop design solutions	0.81	0.92
Select the best possible design	0.59	0.84
Construct a prototype	0.68	0.88
Evaluate and test a design	0.75	0.93
Communicate a design	0.65	0.85
Redesign	0.79	0.94
Cronbach's alpha value	0.88	0.96
Number of factors	1	

Note: 'Item 1. Conduct engineering design' was not included for all the EFA analysis; Item numbers used for each study are identical to those used in the original study.

The final solutions for both studies showed factor loadings above 0.59 for all items. Some items (e.g., develop design solution, evaluate and test a design, and redesign) commonly emerged with the highest loadings in both final factor structures. The item 'identify design needs' demonstrated the highest factor loadings for Carberry [28], but showed the lowest factor loadings in the current study. These results suggest further examination of whether the difference in magnitude of factor loadings is statistically significant. Other results, such as the variance explained, could not be compared as this study only used analysis results reported by Carberry [28].

Conclusions and Future Works

This study examined evidence of score validity and reliability for the usage of the EDSE scale in pre-college engineering education contexts. The analysis yielded a unidimensional factor structure with strong evidence of score validity and factor loadings ranging from 0.59 to 0.81. The resulting factor also showed high internal reliability with a Cronbach's alpha value 0.88. The factor structure found by Carberry [28] in the context of higher engineering education was replicated in the present study, indicating measurement equivalence of the EDSE scale across the contexts of secondary and higher engineering education.

Future work includes confirmatory factor analysis (CFA) after additional administration of the survey with a new cohort of students. This additional validity step will hopefully allow the research team to consider the engineering design self-efficacy of students enrolled in the [PROJECT NAME] course. This is particularly interesting considering the demographic characteristics of this study's sample of secondary school students relative to current engineering enrollments in higher education [29]. Exploring these demographic differences may shed light on the structural invariance of the EDSE scale across different student groups.

Another opportunity for further work includes the integration of these quantitative findings with qualitative data examining students' self-efficacy in performing engineering design processes within the e4usa program. A mixed-methods study is currently on-going to investigate contributing factors to students' self-efficacy in the engineering design process in connection with the e4usa curriculum and its implementation.

Results from this work provide the foundation to support the usage of the EDSE scale for secondary school students, introducing a measurement of engineering design self-efficacy to the pre-college engineering education community. This work also indicates a need for replication and reproducibility studies within the engineering education community that is particularly important given the recent growth in the number of engineering design courses emerging at different levels of pre-college education [30]-[31].

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