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Revisiting a Measure of Engineering Design Self-Efficacy*

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An important step in the growth of engineering education as a unique field of inquiry is to understand how theoretical constructs manifest within different engineering contexts. Replication and reproducibility studies should be conducted to support and ensure results are valid and generalizable across different variations of the same context, and to support and ensure research in engineering education maintains an integral role in the development of future engineers. This study follows the previous work of Major and Kirn to replicate and re-validate Carberry and colleagues' work to create an engineering design self-efficacy instrument. Exploratory and confirmatory factor analyses of data collected from students enrolled in active learning environments reveal that students' confidence and perceived success to complete design tasks combine into a single factor. Additional work is needed to further explore this emergent inconsistency and refine the model used to assess engineering design self-efficacy.

Keywords: engineering design; self-efficacy; study replication and reproducibility

1. Introduction

Engineering education is a growing area of scholarship around the world as demonstrated by the emergence of doctoral programs, societies, conferences, journals, and research agendas [1–7]. Research conducted within the general context of engineering education has been described as a discipline, community, or field [8, 9]. The inability to differentiate between how we describe engineering education and other similar research suggests a continual need to assess what has been done both within and outside of engineering education research. Available reviews and meta-analyses of current and emerging research methods [10–13] as well as publication patterns [14, 15] provide steps to develop engineering education as a rigorous discipline [7, 16]. Emerging from this literature is the call for replication and reproducibility of previous findings, which are actions considered central in scientific research [17]. Such actions should be considered paramount when discussing research design [18-19] in order to ensure implications for various types of validity evidence [20]. Replication and reproducibility studies should be conducted to determine how results established in one context might generalize to others, and to ensure that previously established results align with updated markers of quality. Shifts have been seen in engineering education related to quality in qualitative research [21–23] since calls for replicability and reproducibility studies first came forth [24, 25], but these shifts are just beginning within quantitative research.

The sub-community of quantitative researchers within the engineering education research community must advance and mature engineering education scholarship by conducting replication and reproducibility studies aligned with updated markers of quality. Study replication serves to prove, disprove, or clarify earlier results reported in the literature. Such a demonstration through replication supports the broader need for education research [26], which ensures research remains an important part of the development of future engineering students [27]. This paper provides one example to reproduce and replicate the original findings from the often used and well cited Engineering Design Self-Efficacy (EDSE) scale developed by Carberry and colleagues [28, 29]. The context for this replication and reproducibility study within active learning environments is first outlined by the foundations of self-efficacy and the EDSE instrument. We also highlight the ways the instrument has been used since its initial publication in 2009.

2. Background

2.1 Self-efficacy

Self-efficacy is a task-specific construct concerned with an individual's belief in their ability to execute behaviors resulting in a desired level of performance [30–32]. The task-specific nature of self-efficacy reveals a need to create specific measures to assess self-efficacy that are specific to certain domains, because one cannot assume that someone displaying low confidence in one domain is automatically inefficacious toward another domain [31]. Numerous efforts have been undertaken to understand the role of self-efficacy in engineering education [29, 33–49]. These studies have developed a variety of instruments to measure self-efficacy for specific engineering-related tasks.

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2.2 The Engineering Design Self-Efficacy (EDSE) Instrument

The EDSE instrument was designed to measure self-efficacy within the domain of engineering design [28, 29]. EDSE is a student's confidence to conduct design activities. The EDSE was initially presented to the engineering education community in 2009 [28] and then later refined in 2010 [29]. The initial impetus for development of this instrument was to investigate the assumption that experience through completion of engineering tasks increased self-efficacy toward engineering design activities. Carberry, Lee, and Ohland [29] designed the instrument to be malleable to the needs of the surveyor by embedding flexibility in the constructs and items used. A generic scale question was used to rate any number of task-specific self-concepts of interest. The primary self-concept of interest was self-efficacy (presented as confidence), but also included motivation, expectancy for success, and anxiety [28, 29]. These secondary self-concepts were included to test theoretical relationships and are not limited to those selected. Each scale consisted of a set of items based on a chosen representation of the engineering design process. The design process selected for the EDSE involved eight steps, resulting in eight items per scale. The eight items could be modified or replaced with statements aligned with alternative engineering design process representations. A check of effectiveness for the eight items, written to represent the chosen design process, was embedded in the instrument as a generic ninth item: conduct engineering design. This single item provides a means to test any set of items written for any given engineering design process; factor analysis should produce a single factor representing engineering design that correlates to the additional generic item.

The results reported by Carberry, Lee, and Ohland [29] demonstrated three important findings. First, the chosen engineering design process representation can appropriately measure task-specific self-concepts, such as self-efficacy. Second, EDSE is highly dependent on past engineering experiences. Third, motivation, outcome expectancy, and anxiety toward engineering design correlate highly to EDSE.

2.3 Use of the EDSE Instrument

Almost a decade later, the EDSE instrument has been used or referenced over 200 times by numerous journals, conference proceedings, dissertations, and engineering education educators (e.g., [50–54]). One relevant example to this study is a quantitative study by Major and Kirn [55], which sought to use the EDSE instrument [29] to explore changes in student design self-efficacy as a result of participation in active learning environments, such as problem- and project-based learning. A later study by Major and Kirn [56] also qualitatively investigated how the active environment itself might bring about those attitudinal changes. Results of exploratory factor analysis (EFA) by Major and Kirn [55] suggested that students might see confidence and success to be the same factor, i.e., feelings in their ability to competently complete design tasks. The authors recognized that such a combination has similarly been seen in engineering identity analyses (performance-competence) as an important part of engineering identity development when mediated by interest or external recognition [57], such as what might be developed in active learning environments [58]. The model was subsequently reduced to three-factors: (1) confidence-success, (2) motivation, and (3) anxiety [55]. The authors followed factor analysis with pre-post comparative analysis and found that students had a significant increase in confidence-success over the course of the semester. In their discussion, it was thought that active learning might allow students to develop attitudinal feelings of confidence and success, such that it might also be developing students' identities as engineering designers [56].

3. Purpose of the Study

This study re-examines the validity evidence presented for the EDSE instrument by Carberry et al. [29] and preliminary work of Major and Kirn [55] through a replication and reproducibility effort within the context of active learning. New validity evidence for the EDSE instrument was generated using new analyses to support the continued use and potential modification of the instrument. The results expand and complement the initial validity work done to develop the instrument. This overall effort was guided by the following research question: *RQ: How does previous validity evidence for the Engineering Design Self-Efficacy instrument compare to new emerging evidence within active learning environments?* The results provide a replication and reproducibility study of motivational constructs within engineering education. Insights from continuous evaluation within and outside of engineering education build a strong foundation for use of the instrument across multiple populations.

4. Methodology

The work of Major and Kirn [55, 56] examined changes in student EDSE due to participation in a single project-based learning statics course. This study sought to replicate this earlier work, and to expand it to three other courses using similar and different active learning practices, to determine whether further validity evidence in an active learning environment could be obtained. We start by describing the courses that were used.

4.1 Research Setting

Four separate courses at the same western land-grant university were used for this study. Courses were chosen by solicitation to instructors of well-known, high-enrollment, active-learning courses at the university that would represent the breadth of active learning courses that might exist. We describe each of these courses below as we believed the different context and style of active learning might result in slight variations other than what we present.

(1) Introduction to Mechanical Engineering (1st-year, 8 sections, n = 287): This course used a lecture and lab split. The lecture portion of the course involved students discussing practical engineering topics. Students worked in and out of class on LEGO Mindstorm-based [59] projects and other real-world applicable engineering projects (e.g., helmets that protect a user from impact-related G-Forces). Each team project was tested and required students to document their design processes. The lab portion of the course allowed students to learn three-dimensional design. Students used SolidWorks [60] and completed both in and out-of-course modeling projects. The relevance in surveying this course is its use in early pilot work to test the original EDSE instrument [28–29].

(2) Engineering Statics (2nd-year, 1 section, n = 246): This course used both problem and project-based learning with innovative strategies for assessment. The instructor used lecture for a small portion of each class period to discuss basic theory before moving onto exercise problems. Students were given time to attempt the problem alone and with the assistance of students around them before the instructor proceeded to solve the problem on an overhead. The instructor assessed student competence in completing engineering problems using first-to-five strategies [61] prior to solving the problem. The last three weeks of the course were dedicated to a project requiring students to work in teams to design, analyze, build, and test a balsa bridge within material and size limitations. The relevance in surveying this course is its use in earlier work by Major and Kirn [55, 56].

(3) Dynamics (2nd-year, 1 section, n = 159): This course primarily implemented problem-based and experiential learning. The course provided short lectures each day that were followed by supplemental problems, videos, or experiments. The problems presented used real-life examples to link in-class content to out-of-class engineering scenarios. The experiments required students to use specific measurement tools to find an unknown value (e.g., use of a stopwatch, yardstick, and two skateboards to design a momentum experiment that allows the student to determine a close estimate of the professor's mass). The relevance in surveying this course is its use in early pilot work to test the original EDSE instrument [28–29].

(4) Solid Mechanics (3rd-year, 2 sections, n = 174): This fully flipped course typically used a small lecture followed by completion of homework problems in groups. Instructors and supplemental instructors were available for additional assistance during problem-solving activities. Students were required to attend mechanics demonstrations, watch additional lecture videos, and complete step-by-step problem-tutorial videos called MecMovies [62] outside of class. This course was not used for pilot work or earlier work by Major and Kirn [55, 56].

4.2 Participant Sample and Demographics

The total unique-student population was determined by comparing rosters for all four courses to identify students enrolled in multiple courses. The subsequent population totaled 684 unique students, when accounting for dual-enrolled students. A sample of 383 students completed the pre-survey (56.0% response rate) and 290 students completed the post-survey (42.4% response rate). Demographics of the students who completed each survey, including their self-reported race/ethnicity, gender, and sexual orientation are shown in Table 1.

Participants' self-identified demographic information was collected to compare student groups across courses, academic year, race/ethnicity, gender, and sexual orientation. Some categories were collapsed to protect the identity of our participants. Our participant population is primarily heterosexual, White, and male. We recognize that this group of participants is not representative of the full diversity of engineering [63].

4.3 Survey Administration

A modified online version of the EDSE instrument [29] was administered to students using Qualtrics [64] at the beginning and end of the Spring 2016 semester. Students were offered varied course incentives depending on the course(s) they were enrolled in to compensate their participation (Table 2). Students enrolled in more than one

Table 1. Demographics of pre- and post-survey responses to the EDSE instrument are shown by course enrollment, year of academic enrollment, self-identifying race/ethnicity, self-identifying gender, and self-identifying sexual orientation

	Pre-Survey	Post-Survey
Total Response	381	297
Course		
Intro to Mech. Engr.	118 (31%)	75 (25%)
Engineering Statics	162 (43%)	122 (41%)
Engineering Dynamics	111 (29%)	117 (39%)
Solid Mechanics	130 (34%)	131 (44%)
Year		
1st Year	86 (23%)	48 (16%)
2nd Year	177 (46%)	158 (53%)
3rd Year	102 (27%)	81 (27%)
4th Year or more	16 (4%)	10 (3%)
Self-Identifying Race/Ethnicity		
American Indian or Alaskan Native	10 (3%)	5 (2%)
Asian	53 (14%)	39 (13%)
Black/African American	14 (4%)	7 (2%)
Hawaiian or Pacific Islander	17 (4%)	12 (4%)
Hispanic, Latinx, or Spanish	54 (14%)	40 (13%)
Middle Eastern or North African	3 (1%)	0 (0%)
White/Caucasian	279 (73%)	224 (75%)
Another Race/Ethnicity	6 (2%)	4 (1%)
Self-Identifying Gender		
Female	67 (18%)	55 (19%)
Male	305 (80%)	239 (80%)
Transgender or Another Non-binary	19 (5%)	10 (3%)
Self-Identifying Sexual Orientation		
Heterosexual/Straight	357 (94%)	278 (94%)
Another Orientation	16 (4%)	15 (5%)

Table 2. Students could receive one or more incentives from different course instructors and the research group for their participation in completing pre- and/or post-surveys

Course	Course-Offered Incentive
Engineering Statics	5 points of extra credit (on a 1000-point scale) to complete each survey outside of class time.
Introduction to Mechanical Engineering	No course-offered incentive was provided. Students were given 20-minutes of in-class time to complete the survey.
Dynamics	5 points of extra credit (equivalent to one homework assignment) to complete each survey outside of class time.
Engineering Solid Mechanics	1% bonus to final semester grades for completion of both surveys outside of class time.

course did not have to take the survey more than once to receive the benefits for each course. All duplicate responses were removed before our analysis took place. Participating students were also given an extra opportunity from the research team to receive a $10 electronic gift card for their participation.

Students were asked to rate their confidence to design, motivation to design, perceived outcome of success doing design, and anxiety to complete varying design tasks on a 11-point scale from 0 to 100 (Fig. 1). Responses were analyzed by converting the 11-point scale from 0 to 100 to 0 to 10 as was done in the earlier work of Major and Kirn [55]. Additional open-ended questions were included to provide in depth qualitative insights and demographic infor-

Item Names	Item	Scale										
		0	10	20	30	40	50	60	70	80	90	100
Conduct Engineering Design	1	O	O	O	O	O	O	O	O	O	O	O
Identify a design need	2	O	O	O	O	O	O	O	O	O	O	O
Research a design need	3	O	O	O	O	O	O	O	O	O	O	O
Develop design solutions	4	O	O	O	O	O	O	O	O	O	O	O
Select the best possible design	5	O	O	O	O	O	O	O	O	O	O	O
Construct a prototype	6	O	O	O	O	O	O	O	O	O	O	O
Evaluate and test a design	7	O	O	O	O	O	O	O	O	O	O	O
Communicate a design	8	O	O	O	O	O	O	O	O	O	O	O
Redesign	9	O	O	O	O	O	O	O	O	O	O	O

Fig. 1. Students rated their confidence, motivation, perceived ability to succeed, and anxiety to complete design tasks on an 11-point EDSE scale from 0 to 100.

mation. This article focuses only on the quantitative findings.

4.4 Factor Analysis and Structural Equation Model Fit

Previous EFA and correlation testing suggested that students saw confidence toward design and perceived outcome of success designing as a single construct [55]. Additionally, earlier pairwise t-testing of a combined confidence-success model revealed that students had a significant increase in the combined construct over the course of a semester [55]. The current study completed EFA again, using parallel analysis for both the pre and post data using R Statistical Software [65]; Promax rotation [66]; and 0.50 factor loading cutoffs [67]. Items within the confidence and success factors were averaged (i.e., confidence item 1 with success item 1, etc.) to create a combined confidence-success factor prior to analysis (see previous work by Major and Kirn [55]). Pre- and post-survey factor scores were checked for construct reliability using a recommended value of 0.70 for Cronbach's α [68, 71]. Individual confidence and success factors were also tested to ensure that consistency was sufficient before and after averaging. Finally, resulting factor scores were created by averaging items within the factor, according to the EFA, which were later checked for correlations.

The idealized model was then modeled using confirmatory factor analysis (CFA) using the R statistical software package, *lavaan* [70]. The recommended sample size for CFA is 10 participants per item; a total of 360 participants for this study [71]. Since our total sample was near or below the desired 360 responses, a Kaiser-Meyer-Olkin (KMO) Test was run to check for sample adequacy [72]. Further, to abide by homogeneity of variance, a Bartlett Sphericity Test was run [73]. Steps were undertaken before each iteration of fit to ensure that items continued to correlate to the model's main three factors found during the EFA. We considered items to be highly correlated if they had a factor loading of above 0.60 [74]; those items below this threshold were removed. *Modindices* [70] were additionally inspected throughout for items considered to be largely affecting the model Chi-Square (X^2).

We determined model fit by comparing *lavaan* fit values [71] to those recommended in the literature, including a Normed Fit Index above 0.9 or 0.95 (NFI) [75, 76], Goodness of Fit Index above 0.90 (GFI) [75], Comparative Fit Index above 0.93 (CFI) [75], Root Mean Square Error Approximation under 0.06 (RMSEA) [77] with the upper confidence level of the RMSEA lying under 0.08 [77], and a Relative Chi-Square Value under 2 or 3 [74, 79]. *Modindices* [70] were then used based on findings and consideration of the theoretical models to determine and create covarying pathways to better achieve model fit values. Updated models were compared to the model without the update using a Vuong's Test [80] to test for significant improvement. Our process of model improvement ceased when we no longer found significant improvement (determined by absence of a significant Vuong's Test *p*-value) using the largest sensical *modindices* recommendation [70].

5. Results

5.1 Exploratory Factor Analysis

Parallel analysis, shown in Fig. 2a and 2b, suggested that the model should contain three factors in both the pre- and post-versions, respectively. Following these recommendations, we used a three-factor model for continued EFA.

The EFAs of both pre- and post-data, shown in Table 3, present identical factor structures: a confidence-success (CS) factor made of all the confidence-success items, a motivation (M) factor made of all motivation items, and an anxiety (A) factor made of all the anxiety items. Within item numbering is still identical to that found above in Fig. 1.

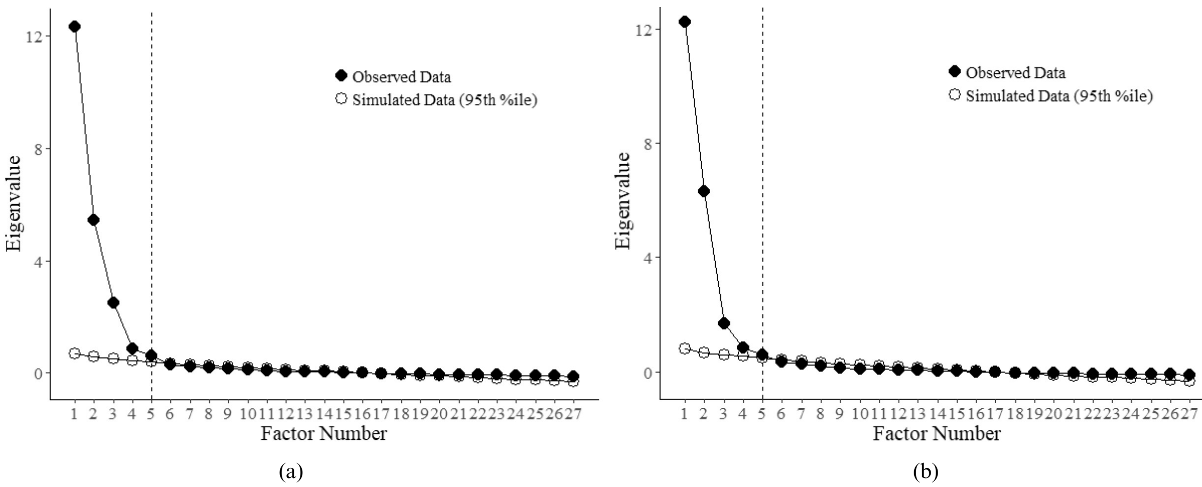

Fig. 2. Like in Major and Kirn [55], results of parallel analysis suggest that there were three latent factors in both the pre- and post-versions, respectively.

Table 3. Through exploratory factor analysis, we found EDSE items in the pre- and post-survey each cleanly loaded into a three-factor model

Item Code	Pre-Survey EFA			Post-Survey EFA		
	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor
CS1	0.928			0.902		
CS2	0.901			0.863		
CS3	0.808			0.743		
CS4	0.936			0.894		
CS5	0.898			0.904		
CS6	0.755			0.769		
CS7	0.815			0.840		
CS8	0.707			0.596		
CS9	0.851			0.849		
M1		0.820			0.838	
M2		0.852			0.890	
M3		0.833			0.779	
M4		0.924			0.896	
M5		0.897			0.886	
M6		0.844			0.692	
M7		0.878			0.834	
M8		0.721			0.783	
M9		0.756			0.640	
A1			0.884			0.952
A2			0.924			0.945
A3			0.891			0.911
A4			0.939			0.957
A5			0.916			0.898
A6			0.885			0.877
A7			0.899			0.887
A8			0.687			0.742
A9			0.885			0.899

These findings are similar to those found in our earlier work [55].

5.2 Construct Reliability

Construct reliability using Cronbach's α showed that the respective reliability for pre- and post-test self-efficacy (0.96; 0.96), motivation (0.95; 0.95), outcome expectancy (0.96; 0.96), and anxiety (0.97; 0.97) were sufficiently above the suggested 0.70 loading [69]. The combined confidence-success factor was also sufficiently above the threshold (0.96; 0.95). In combination, these results suggest that the EDSE factors were very reliably measured by the items used in the survey.

5.3 Correlation

A test for inter-factor correlation confirmed that the combined confidence-success and motivation factors were highly correlated for both the pre- and post-survey data (0.597; 0.716). Additionally, we found that confidence (0.361; –0.209) and motivation (–0.242; –0.256) were not highly correlated with anxiety. This finding is in opposition with original findings from Carberry, Lee, and Ohland [29], which suggests a high negative correlation should exist. The overall results support a three-factor grouping of results as our exploratory factor analysis showed.

5.4 Confirmatory Factor Analysis

5.4.1 Kaiser-Meyer-Olkin (KMO) Sampling Adequacy Test

Our use of a KMO test suggested that the number of participants is adequate for the number of items to be tested in CFA (above 0.50) [72]. We found that measured sample adequacy for both pre- and post-survey data was 0.94, which based on Kaiser's work, would be thought of as sample adequacy that is "superb".

5.4.2 Bartlett's Sphericity Test

Our use of Bartlett's Test for both pre and post-survey data resulted in a *p*-value of 0.000, and Chi-squared values of 17,073.01 and 13,066.27, respectively. Significant *p*-value results reject the null hypothesis that the data's correlation matrix is similar to an identity matrix, which suggests that the data has a structure for factor analysis. We used these combined results to move forward with confirmatory factor analysis.

5.4.3 Pre-survey and Post-survey: Model 1

A confirmatory model was tested for both pre- and post-surveys, which used the theoretical structure from the EFA (Table 4). Factor one consisted of all confidence and success items. Factor two consisted of all motivation items. Factor three consisted of all anxiety items. A test of Model 1 for the pre-survey did not result in adequate model fit; however, model summaries suggested that all items were highly correlated to the model. The largest *modindices* still fit theoretical constructs, which suggested that we create a pathway between items C1 and C2 to improve model fit.

We observed similar results for the post-survey Model 1. We found items were still highly correlated to the model and fit measures were very low, except for the GFI which was above the recommendation of 0.9. *Modindices* within theoretical constructs recommended we create a covarying path between items C8 and S8. Both modifications were made within Model 2 for the pre- and post-survey.

5.4.4 Pre-survey: Model 2

The *modindices* for pre-survey Model 1 suggested additional paths between item C1 and C2 be added. Table 4 provides the fit indices that resulted from these changes. We found that small improvements were present, but there was no indication of large fit improvement. We found that data summaries still suggested that all items were highly correlated to the model.

Further, Vuong testing for significant changes between pre-survey Model 1 and pre-survey Model 2 suggest that the addition of the path resulted in no significant change in fit ($p = 1$).

Table 4. The model of EDSE could not be confirmed using confirmatory factor analysis, even when we attempted to improve model fit

		Model 1		Model 2	
Indicator	**Suggested Value**	**Pre-Survey**	**Post-Survey**	**Pre-Survey**	**Post-Survey**
X^2 *p*-value	> 0.05	0.000	0.000	0.000	0.000
X^2 / df	< 2 or 3	> 7	> 5	> 7	> 5
NFI	> 0.90	0.73	0.77	0.74	0.77
GFI	> 0.90	0.75	0.91	0.84	0.91
CFI	> 0.93	0.75	0.81	0.77	0.81
RMSEA	< 0.06	0.13	0.12	0.13	0.12
RMSEA-Upper Tail	< 0.08	0.13	0.12	0.13	0.12

Testing of the alternative null hypothesis that Model 2 was better than Model 1 displayed that Model 1 was significantly better than Model 2 (p = 9.65 × 10^{-6}). These results suggest that model fit improvement using the addition of covarying paths need not continue because the *modindices* recommendation should have resulted in the largest increase in fit and did not end up being significant.

5.4.5 Post-survey: Model 2

The recommendation of *modindices* of post-survey Model 1 suggested an additional path between item C8 and S8 be added. Table 4 provides results of the changes. We found that the addition of a path did not result in significant increases in fit, which was confirmed using Vuong testing (p = 1). We also found testing of the alternative null hypothesis confirmed the same results as the pre-survey hypothesis (p = 9.62 × 10^{-6}). These results, like the pre-survey, suggest that model fit improvement using the addition of covarying paths need not continue. It is with these results that we conclude that the theoretical model of design self-efficacy tested through EFA cannot be confirmed using CFA.

6. Discussion

To our knowledge, none of the over 200 journal articles or conference proceedings using and/or citing the original instrument by Carberry and colleagues [28, 29] has attempted to provide validity evidence to support their use of the EDSE instrument. These works have primarily focused on practical use of the instrument or its theoretical basis in the creation of new scales. This work is the first of its kind to further examine the reliability and validity of previously collected and analyzed data using the EDSE instrument. Initial reliability evidence for the instrument [28, 29] indicated that the factors held together internally. Our reevaluation of this work, considering new standards for quality in quantitative research [25, 81–83], indicated that there is insufficient evidence to extend the original claims of reliability and validity to other contexts. The new reliability and validity approaches applied to the EDSE instrument within this work (e.g., CFA) represent exploration of not only the internal consistency of the items, but also the uniqueness of each factor from one another. It is due to the lack of a reliable structure of the instrument that we call for additional efforts in establishing an instrument with improved accuracy toward measuring students' EDSE. We use the remainder of the discussion to highlight the potential reasons that may have caused these findings to emerge when the EDSE instrument was designed to mimic established measures of motivation in other disciplines.

6.1 Inconsistencies in Measuring Motivation in Engineering

The results of our study that question the use of an existing motivation measure in engineering are not unique. Multiple studies have demonstrated that engineering students do not behave the same, or embody the same motivational beliefs, as other students in similar courses. Nelson, Shell, Husman, Fishman, and Soh [84] found that non-engineering students better connected their futures with their current course, had greater perceived instrumentality for the course content, and espoused more learning-oriented goals for their academics, than engineering students enrolled in the same technical course. Similarly, leading motivation researcher and social psychologist, Judith Harackiewicz, noted that engineering students enrolled in a technical course with other non-engineering majors demonstrate significantly less interest [85]. Kirn and Benson [86] found that engineering students' conceptualizations of grit differed from the theoretical definition of persistence toward long-term goals [87]. The engineers' conceptualized grit as persistence on short-term tasks which differs from Duckworth, Peterson, Matthew, and Kelly's [87] traditional focus on long-term goals. The inconsistencies in student expression may begin to explain why the engineering education research community has struggled to consistently use motivation frameworks in their studies of student motivation [88].

6.2 The Limitations of Transferring Motivation Measures across Cultural Boundaries

We note that the lack of continuity of findings between different survey administrations is not unique to engineering. Universal application of educational psychology theories has been called into question [89], especially in the context of race/ethnicity and culture [90–92]. Artelt [93] found that different cultures have different meanings for intrinsic and extrinsic motivation. Schunk, Meece, and Pintrich [91] described how expectancy-value theory is constrained by the social and cultural beliefs of the culture; what one person from one culture values is likely different from what another person from another culture values. Zusho and Clayton [92] found that achievement goal theory was especially bound by culture because the achievement goal framework had only been researched in Western cultural contexts. These cultural-values are embedded in this and other similar theories. Further, there is a growing body of evidence indicating that motivational constructs as designed are not robust when transferred into unique cultural domains such as engineering. It is not surprising then that the EDSE instrument has limited reliability and validity when considering this body of work.

6.3 The Uniqueness of Engineering Culture

Work has noted that motivation theories have limited generalizability across cultural boundaries. Significant work in engineering has described the unique culture of engineering [94]. The field has been described as having an engineering way of thinking, engineering way of doing, being an engineer, acceptance of difference, and relationships [95]. Additionally, engineering is perceived as an industry-driven field (in other words, practical solutions must be generated) that divides the technical from the social aspects. The socio-technical divide manifests in the valuing of technical skills (e.g., problem solving and differential equations) over professional skills (e.g., communication and interpersonal skills) [95, 96]. This divide, described as the depoliticization of engineering, manifests in educational environments that celebrate the perceived removal of the social components that drive the need for engineers in the first place [95-96]. The prioritization of the technical leads to the continued reconstruction of a culture rooted in technical meritocracy, i.e., reward based on technical ability. Such technical meritocracy has been prioritized by the engineering community, but has also been shown to stifle creativity [97], disproportionately reward those who fit the traditional engineering mold, and exclude potential new members to the engineering profession [98, 99]. These cultural values and priorities drive the development of communities of practice, accreditation processes, and individual level priorities that directly impact engineering students and serve to shape students' motivations [95, 96, 98].

These values fortified by cultural structures become embedded in students' epistemological understanding of engineering, i.e., what counts as legitimate engineering knowledge, tools, and practices [98]. Student motivations, goals, and actions are all influenced by their desire to become a part of or enter specific communities of practice and be rewarded by those who hold access to the engineering profession [57, 84, 86, 96, 99, 101–103]. Training students in a technically driven culture that does not favor socio-cultural components shapes how students are motivated in engineering and motivated to be engineers. Student motivation then becomes filtered due to the culture of engineering and its inherent value system, which shapes how students interpret and respond to motivational research that is in itself shaped by the culture. It is therefore not at all surprising that the EDSE instrument did not hold together when tested for reliability and validity.

7. Limitations

There are several limitations to this replication study beginning with our sample. We acknowledge that our sample size is not ideal even though KMO testing indicated we had a large enough sample size to model EDSE effectively using factor analysis. Our sample is also acknowledged as predominantly White, male, and heterosexual, and may not be representative of the current engineering community or the diversity goals of the engineering education community [63].

Further limitations come by way of the differences between the methodological approaches used in this study compared to those used by Carberry and colleagues' [28, 29] original work creating the EDSE instrument. The original approach taken was to provide content, criterion-related, and construct validity evidence using an available engineering design process, past engineering experience of participants, and Bandura's Self-efficacy Theory [30–32] as validity sources. The items and scales were consistent between studies; however, factor analysis to determine item inclusion was conducted quite differently. The original work examined each scale individually and concluded after exploratory factor analysis. The results suggested one factor for each scale – self-efficacy, motivation, expectancy for success, and anxiety. The current article did not differentiate between scales or constructs, which revealed a three-factor model. The discrepancy between studies was that one factor emerged for confidence and expectancy for success during exploratory factor analysis. This study attempted to confirm these findings with confirmatory factor analysis. Results did not converge, which suggests more work is needed. A preliminary comparison of fits between a three and four-factor model showed that a three-factor model still maintained a higher level of fit. We do not present these differences in this study as neither model met thresholds for quality. Correlations between factors and tests for reliability were conducted for both studies with an additional step taken in the original work to examine the relationship between the factor consisting of multiple items, i.e., engineering design process steps, and a single item referring to engineering design. The studies continue to diverge in terms of how the original work expanded its analysis by grouping participants based on engineering experience – high, intermediate, and low self-efficacy [29]. Such groupings were used because the sample included more than just engineering students. One-way ANOVAs complemented by Tukey HSD post hoc comparisons were used to compare group scores for self-efficacy, motivation, outcome expectancy, and anxiety toward engineering design to examine and confirm criterion-related validity. Group scores were not compared in this study because our model does not hold as initially theorized.

8. Conclusion and Future Work

This study set out to explore students' EDSE in active learning environments. We administered the EDSE in four classes using active learning methods to gather additional validity evidence. Results of this testing indicated that the survey does not meet reliability and validity standards for the population in our study. We believe potential explanations for this finding are supported throughout ongoing conversations in the educational psychology literature, that suggest motivation measures do not transfer well across contexts. Our findings indicate that further work is needed to establish the EDSE instrument (or another measure) before using the EDSE instrument again to ensure that the measure accurately reflects students' self-efficacy toward engineering design.

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