ASEE 2022 ANNUAL CONFERENCE
Excellence Through Diversity
MINNEAPOLIS, MINNESOTA, JUNE 26TH-29TH, 2022 ASEE

Paper ID #36986

Validity Evidence for Exposure and Motivation Scales in a Microelectronics Workforce Development Program

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Abstract

Microelectronics play an increasingly important role in a wide range of technologies, which include not just computers but many consumer, business, and defense capabilities. To ensure a reliable source of microelectronic chips in the future, it is crucial to train an increasing number of students in this area and to foster their connection with the industry and government employers. As training programs are being stood up now, it is important to determine whether they are effective in meeting these goals. Our team modified an existing assessment of students' exposure and motivation to focus explicitly on topics in microelectronics. The purpose of this paper is to evaluate validity evidence in terms of item functioning and factor structure. Specifically, we ask: 1) *To what extent do the Exposure and Motivation items function as intended (i.e., items written to be exposure factor together and items written at motivation factor together); 2) To what extent are the items measuring Exposure and Motivation in microelectronics in a sensitive way (i.e., the items are able to detect the expected variance among students)?* The assessment was administered as a pre- and post-survey to undergraduate engineering students in an introductory engineering design course (n = 508). Confirmatory factor analysis (CFA) was performed to compare the model fit for several models. Results from the CFA in terms of factor structure and goodness of fit confirm the two scales, *Exposure* and *Motivation*, are consistent with the original instrument. An item response theory (IRT) model was found, which indicated the two scales can sensitively measure differing levels of motivation and exposure. This study provides an assessment with validity evidence that it can be adapted for different technical areas and still provide meaningful information regarding students' exposure and motivation in a specific area.

Introduction

Microelectronics play an increasingly important role in a wide range of technologies, which include not just computers but many consumer, business, and defense capabilities. The increasing role of microelectronics has led to the consolidation of the industry and increasing dependence on a shrinking number of suppliers (Brine, 2018). At the same time, the demand has been growing rapidly, with an overall growth expected at 15.7% in 2021 alone (International Data Corporation, 2021). As of 9 November 2021, indeed.com lists a total of 21,370 job posting in areas related to microelectronics, such as semiconductor manufacturing, semiconductor design, semiconductor testing, and semiconductor packaging, indicating rapid growth in the semiconductor and packaging areas that is outstripping the national talent pool.

With a greater demand for employees with specialized skill sets in microelectronics fields, there is an increasing need for training programs that allow students to develop these specialized skills and foster connections with public and private employers. Workforce development programs are becoming a more frequent way of developing student skills and recruiting into specialized technical fields. These programs have identified a need for a support in a range of levels of education, from Associate's through Ph.D. degrees and continuing education. Knowledge, skills, and abilities needed include a range of general skills associated with semiconductors, as well as specific topics such as secure manufacturing, supply chains, and fields related to the physics of extreme environments (such as ionizing radiation, extreme temperatures, and more).

Several examples of such efforts include the Office of the Under Secretary of Defense (OUSD) Acquisition & Sustainment Industrial Base (IBAS) program, which now leads the National Imperative for Industrial Skills program and the Research & Engineering Trusted & Assured Microelectronics program. These initiative support several University-run programs including SCALE as part of a Public, Private, and Academic Partnership (PPAP), and the START-HBCU program to increase research collaborations between Sandia National Laboratories and several major HBCUs nationwide (U.S. Department of Defense, 2020; Sandia National Laboratories, n.d.). Important aspects of such models include defining a common goal by gathering input from stakeholders on specific workforce needs and operating joint programs with active participation by all members. Success of these efforts particularly depend on academic leaders, not only to run these programs but to support student involvement. Academic partners need to let students know about these opportunities and to increase their interest starting very early in their education, while they are still undecided about their career choices. Attractive aspects of these opportunities for students include higher levels of stability (30 years or more) and the opportunity to work on a wide range of interesting, important and socially beneficial projects. As these programs are being stood up, it will be critical to determine whether they are actually effective in meeting these goals and what programmatic aspects can be improved.

One of the major challenges to workforce development in microelectronics is the limited awareness and exposure most students have to specific areas of microelectronics. For example, topics of radiation hardening, systems on chip, heterogenous integration and advanced packaging are not typically presented in introductory level engineering courses. Following Social Cognitive Career Theory (Lent, Brown, & Hackett, 2002), students must have multiple exposure opportunities to increase their awareness and motivation of working in a given field. By increasing student motivation, students are more likely to consider that field as a realistic career option. If engineering students have little to no awareness of specialized topics in microelectronics while deciding their majors and internship/coop experiences, they are not likely to purposefully pursue a career in microelectronics. Therefore, formative assessments of the ongoing programs are needed to understand the exposure and motivation of students to enter this field and to guide future program efforts. The purpose of the present study is to evaluate initial validity evidence of an assessment of students' Exposure and Motivation in Microelectronics Careers. We ask the following questions: 1) *To what extent do the Exposure and Motivation items function as intended (i.e., items written to be exposure factor together and items written at* *motivation factor together); 2) To what extent are the items measuring Exposure and Motivation in microelectronics in a sensitive way (i.e., the items are able to detect the expected variance students would have)?*

Background Literature

Social Cognitive Career Theory (SCCT) (Lent, Brown, & Hackett, 1994) is a highly cited theoretical framework for understanding why people choose and persist in their career paths. The framework has been studied for over 25 years and has been empirically validated for understanding personal choices in career interest and persistence for many different contexts. For example, SCCT has been utilized to study career development for people with minoritized ethnic and racial backgrounds (Byars-Winston & Rogers, 2019; Cadenas et al., 2020), minoritized gender and sexual identities (Tatum, 2018), first generation undergraduate students (Garriott et al., 2017), people with disabilities (Pham et al., 2020), and low socioeconomic status individuals (Pulliam et al., 2017). Additionally, SCCT has been heavily used to understand the career paths of historically underrepresented populations in STEM fields (Fouad & Santana, 2017; Hardin & Longhurst, 2016; Lent et al., 2018; Turner et al., 2019).

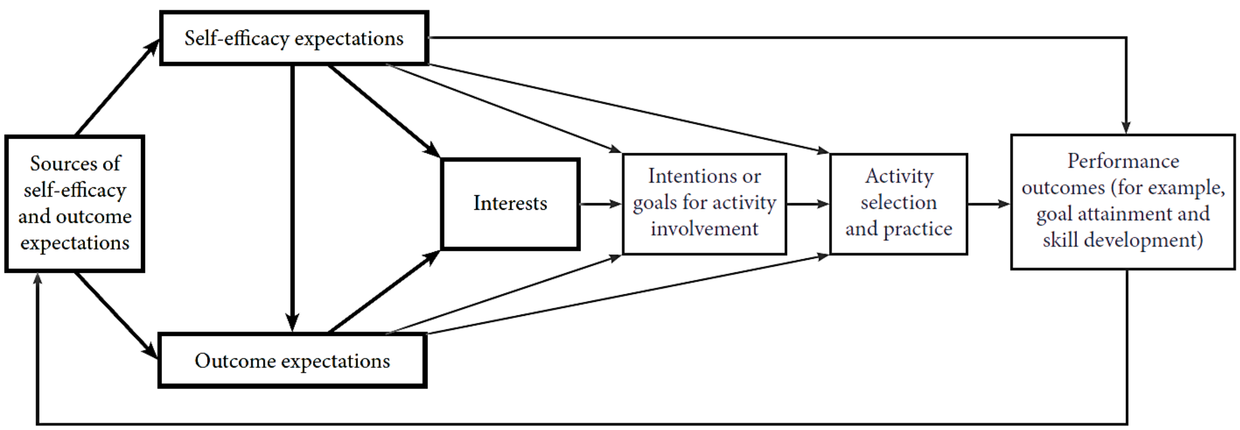
SCCT explains how career choice is formed based on five key factors: self-efficacy, outcome expectations, personal interests, choice goals and actions, and performance domains and attainments. In SCCT, self-efficacy and career outcome expectations, in combination with environmental and personal factors, develop career interests and career choices. Positive learning experiences and accomplishments that build confidence in one's ability to be in a career (self-efficacy) and positive expectations about the impacts of a career (outcome expectations), build awareness of and develop ones' interest in that career (Lent, Brown, & Hackett, 2002). From the perspective of career interest, one is more likely to make goals and choose activities that lead to new skills and outcomes related to that career. Ideally, these new skills and performance outcomes will become new sources of self-efficacy and career outcome expectations.

In Lent, Brown & Hackett's (1994), the SCCT Interest model (Figure 1) hypothesizes that career interest built by past and current sources of self-efficacy and outcome expectations influences ones' motivation to develop and pursue goals and select and engage in specific career activities. These choices impact the goals achieved and skills acquired related to ones' career. Two additional factors related to career interest inherent to SCCT are exposure and motivation. In order to build career interest, one must have multiple exposures that act as sources of positive self-efficacy and outcome expectations. Exposure is the participation in activities related to a potential career that develop into career interest and choices. Motivation is the future interest and choices one makes regarding their career. Career motivation, based on career interest, influences goal and activity choices.

Other researchers have focused on students' awareness of specialized areas in engineering, such as nanotechnology. For example, Dyehouse et al.'s (2008) *Nanotechnology Awareness Instrument* examines two factors, *Exposure* and *Motivation*, impacting students' career interest and goals. Students' exposure and motivation are measured by asking students about the activities they engaged in related to nanotechnology. Dyehouse et al. (2008) define *Exposure* as the "activities that a student has actually completed" such as reading, watching and engaging in the topic (2008, p. 503). They define *Motivation* as "nano-related studies or work that a student plans to do in the future" such as interest in reading, taking courses and pursuing career-related opportunities in the field (2008, p. 503). We utilized the *Nanotechnology Awareness Instrument* for its connection to SCCT's career interest and goal development.

Figure 1.

Model of How Career Interest Develop from a SCCT framework.



Note. Image recreated from Lent, Brown & Hackett (1994).

Methods

Instrument, Setting and Participants

The *Motivation and Exposure in Microelectronics* instrument (Table 1) was adapted from the *Nanotechnology Awareness Instrument* in Dyehouse et al. (2008) for microelectronics workforce development context. In addition, a filter question was added to the survey which stated, "*If you are reading this survey, please select Agree.*" Overall, 508 number of students completed the *Motivation and Exposure in Microelectronics* survey. The survey was distributed once as a post-survey in spring of 2020 (*n* = 226) and as a pre- and post-survey in fall of 2021 (*n* = 282). Participants were students in an introductory engineering design course at a large research university. Students were asked to answer free-response demographic questions at the end of the survey, such as gender, race or ethnicity, and a multiple choice question on international student visa status. The student population was approximately 54% White, 27% Asian, 5% Latinx, 4% Two or more races with 50% of students being White and Asian, 4% Indian, 2% Black and 1% Middle Eastern; also, 15% were international students.

Table 1

Adapted Exposure and Motivation items.

Exposure	*What is your exposure to microelectronics? I have ...*
	E.1 Read something about microelectronics.
	E.2 Watched a video about microelectronics.
	E.3 Had one or more instructors talk about microelectronics.
	E.4 Participated in an activity involving microelectronics (e.g. coding problems, lab, project, etc.).
	E.5 Taken at least one university class about microelectronics.
Motivation	*Please read the following statements and select the answer choice that best describes your level of agreement with the statement.*
	M.1 Read something about microelectronics.
	M.2 Investigate fields of study in which I can learn more about microelectronics
	M.3 Take a class about microelectronics
	M.4 Pursue a research opportunity in microelectronics
	M.5 Pursue an internship in microelectronics
	M.6 Pursue a career in the field of microelectronics

Note. Responses were recorded on a 5-point, Likert scale with the following anchors: *Strongly agree, Somewhat agree, Neither agree nor disagree, Somewhat disagree*, *Strongly Disagree*.

Data Preprocessing

Data were cleaned to improve response quality, following the recommendations of Meade and Craig (2012). The two criteria considered for improving response quality were: a) correctly answering the filter question and b) that the total time spent responding to the survey was greater than or equal to 90 seconds. Ninety-three students were removed for not correctly answering the filter question, and one student was removed for completing the survey in less than 90 seconds, which researchers deemed an unacceptably fast response time. This process resulted in negligible missing data. Overall, data cleaning resulted in the removal of 94 responses that did not meet the two quality criteria described above.

Exposure and *Motivation* scores were calculated by summing the responses for each student in each scale and then normalizing their score by the number of items in each scale. Means and standard deviations were calculated for each scale. On average, students had higher *Motivation* (M = 3.1, SD = 1.0) than *Exposure* (M = 2.7, SD = 1.0). Skewness and kurtosis were calculated to examine the normality of the data. Scores for each item were within range (±3, ±10) for future predictive statistical analysis. Additionally, the bivariate correlations between items within each scale were calculated.

Confirmatory Factor Analysis Procedures

Based on the well-defined theory and previous validation studies performed, a performed Confirmatory Factor Analysis (CFA) was conducted. Confirmatory factor analysis requires that the researcher specify the model and constraints, making it well suited for studies with a well-defined theoretical model. The CFA utilized a robust maximum likelihood estimator within RStudio's Laavan package. The estimator was chosen to account for nonnormality in the data with respect to the size of the dataset. The unstructured model and three alternative models, based on the theoretical structure proposed by Dyehouse et al. (2008), were all found through this analysis.

Goodness of fit for the four models was determined based on a combination of: a) Chi-squared ratio, b) Comparative Fit Index (CFI), c) Tucker-Lewis Index (TLI), d) Root Mean Square Error of Approximation (RMSEA) and e) the Standardized Root Mean Square Residual (SRMR). CFI and TLI are comparative fit indices, where the chi-squared for the specified model is compared to the unstructured model; for both CFI and TLI, higher values indicate better fit with acceptable fit being greater than 0.9 (Thompson, 2004). The chi-squared ratio, similar to CFI and TLI, is best understood in comparison to other specified models. A lower chi-squared ratio is indicative of a better fitting model. RMSEA and SRMR are absolute measures of fit, meaning they are not compared to the unstructured model and the best fitting model has the value closest to zero. RMSEA values of 0.08 or less indicate acceptable fit and 0.06 or less indicate close fit. SRMR values of 0.08 or less indicate close fit. After evaluating the three alternate models using the goodness of fit indices, the models' constraints were modified to improve fit indices and then re-evaluated based on model fit and alignment with the theoretical model.

Item Response Theory Procedures

An item response theory analysis was performed to evaluate the item level characteristics of the *Exposure* and *Motivation* scales. Item response theory (IRT) was used to model the relationship between an individual's performance on an item and their overall ability (van der Linden & Hambleton, 1997). Two models were conducted using a graded response model in RStudio's MIRT package (Chalmers, 2012). A graded response model was chosen for its ability to estimate parameters for polytomous scales. The graded response model utilizes a two-parameter model, producing discrimination and difficulty parameters and item response curves for each item (Samejima, 1997). The two-parameter IRT model approximates the likelihood of a respondent selecting that response at a given trait level using:

$$P_{ik}(\theta) = \frac{e^{a_i(\theta - b_{ik})}}{1+e^{a_i(\theta - b_{ik})}}$$

where $P_{ik}(\theta)$ is the probability that a respondent with the latent trait (θ) selects a response option k or higher for item i. The discrimination parameter (a_i) represents the slope of the response curve, and the threshold, or difficulty, parameter (b_i) indicates the 0.5 likelihood of the respondent choosing the response immediately above or below k. Item response curves and discrimination parameters are useful for understanding a scale's ability to detect variance, where items with high discrimination are more likely to sensitively detect changes in an individual's ability (Reise & Haviland, 2005).

Results

CFA Results

A CFA was conducted with the *Exposure* (n = 5) and *Motivation* (n = 6) scales. To best evaluate the fit of the proposed model, three rival models were tested, including the hypothesized model and three alternative models (Thompson, 2004). Results of the rival models can be found in Table 2. The null model is the unstructured reference model, meaning the model freely estimates variances. The null model is reported as a means to compare the improvement of fit between the uncorrelated, unstructured model to rival, specified models. Model 1 loaded all 11 items onto their respective factors, *Exposure* or *Motivation*. Model 2, similar to Model 1, loaded all but one item, *Exposure* item 5 (E.5), on to the two factors. Item E.5, "*Taken at least one university class about microelectronics*" had a low correlation with the other items in the *Exposure* scale. Lastly, Model 3 loaded all 11 items onto the two factors and specified covariances between *Motivation* scale items M.4, M.5, and M.6. These items were allowed to covary as they evoke similar feelings through shared phrases or meanings (Thompson, 2004). For example, *Motivation* scale items M.4, M.5, and M.6, *"Pursue a research opportunity in microelectronics," "Pursue an internship in microelectronics,"* and *"Pursue a career in the field of microelectronics"* have been allowed to covary due to the shared verb "*pursue*." The standardized item level factor loadings for Model 3 are reported in Table 2. The three proposed models were evaluated on model fit and alignment with theory. The goodness of fit statistics for Model 3 indicates a moderately well fitted model (Table 3).

Table 2

Model 3 standardized item level factor loadings.

Factor	**# of items**	**Range of standardized item level factor loadings**
Exposure	5	0.45 - 0.83
Motivation	6	0.71 - 0.90

Most fit statistics, such as chi-squared, CFI, TLI and SRMR, indicate a good fitting model. However, RMSEA falls slightly outside of the range of acceptable fit (RMSEA ≤ 0.08), indicating some misfit of the model. With other fit statistics being within range of good fit and a Chi-square ratio improving with the more specified models, RMSEA for the CFA model might be out of range due to a smaller dataset. Model 3 was selected as the final model based on the best overall model fit.

Table 3

Comparison of CFA fit indices.

Model	***X2***	***df***	***X2/df***	**CFI**	**TLI**	**RMSEA**	**SRMR**
Null Unstructured reference	1541	55	28	-	-	-	-
Model 1 Covariance between factors only	189.30	43	4.39	0.91	0.88	0.12	0.067
Model 2 Covariance between factors only. Exposure item 5 removed.	157.60	34	4.62	0.92	0.89	0.12	0.063
Model 3 Covariance between factors and Motivation items 4, 5 and 6.	118.80	40	2.95	0.95	0.94	0.086	0.056

Item Response Theory Analysis Results

A graded response model was fit to each scale, *Exposure* and *Motivation*, using the standard expectation maximization algorithm with fixed quadrature. Discrimination and difficulty parameters were found for all 11 items. Using Bock (1972) χ^2 IRT estimation method, item-level fit statistics indicated a good fit for most items (RMSEA ≤ 0.08). The small number of items in the scale contributed to sparseness of the data, thus limiting the reliability of goodness of fit statistics. However, Maydeu-Olivares (2005) and Maydeu-Olivares et al. (2011) posit that CFA goodness of fit indices can be used to assess goodness of fit for IRT models. Hence, the goodness of fit used for Model 3, shown in Table 3, will be used as the goodness of fit statistics for the IRT model.

Table 4 contains the parameter estimates from the graded response model for the *Exposure* and *Motivation* scales. From the discrimination parameter (a_i), most items have moderate (a_i = 0.65 – 1.34) to very high (a_i > 1.70) levels of discrimination (Baker, 2001). One items, E.5, has a moderate level of discrimination, meaning this item was less sensitivity to differences in latent ability. Most items have difficulty intercepts that are evenly distributed over 0, indicating an appropriate level of difficulty for students at all ability levels. Specifically, the placement of the difficulty intercepts indicates that the *Exposure* and *Motivation in Microelectronics* instrument is sensitive to measuring differences in higher levels of latent ability. Item E.5 has high levels of difficulty compared to other items, shown by difficulty intercepts all being shifted to be greater than 0.

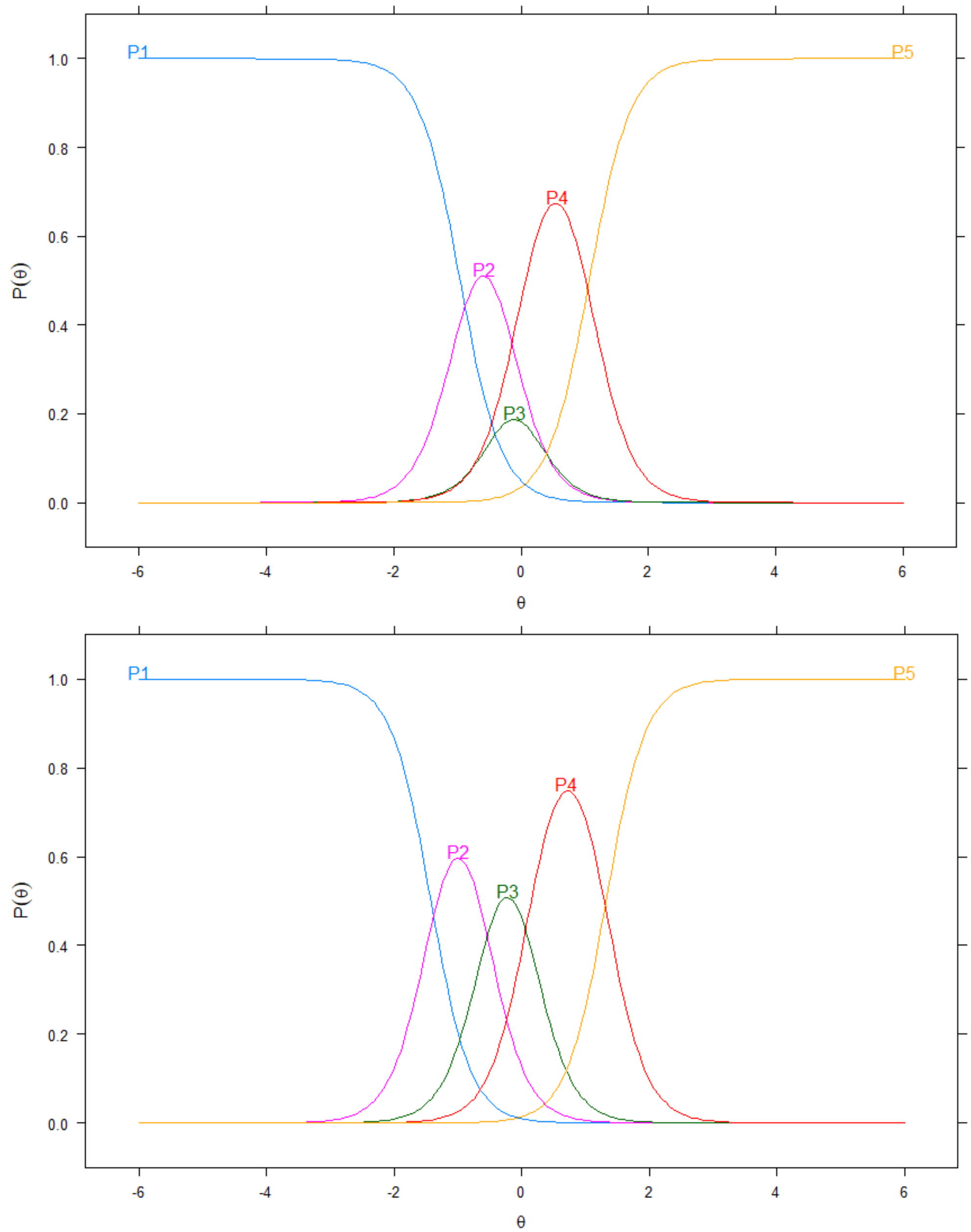
Table 4

Parameter estimates of 2-parameter graded response model for the exposure and motivation factors.

	Item	a_i	b_1	b_2	b_3	b_4
Exposure	**E.1** Read something about microelectronics.	3.35	-1.17	-0.37	-0.16	1.16
	E.2 Watched a video about microelectronics.	2.80	-0.88	-0.10	0.16	1.16
	E.3 Had one or more instructors talk about microelectronics.	2.11	-0.89	-0.032	0.46	1.59
	E.4 Participated in an activity involving microelectronics (e.g. coding problems, lab, project, etc.).	1.40	-1.16	-0.38	-0.10	1.48
	E.5 Taken at least one university class about microelectronics.	0.92	0.50	1.80	2.26	3.95
Motivation	**M.1** Read something about microelectronics.	2.00	-2.02	-1.00	-0.22	1.55
	M.2 Investigate fields of study in which I can learn more about microelectronics	3.23	-1.42	-0.57	0.12	1.32
	M.3 Take a class about microelectronics	2.85	-1.40	-0.53	0.21	1.39
	M.4 Pursue a research opportunity in microelectronics	2.97	-1.36	-0.32	0.56	1.53
	M.5 Pursue an internship in microelectronics	3.68	-1.23	-0.30	0.54	1.42
	M.6 Pursue a career in the field of microelectronics	4.53	-1.06	-0.15	0.75	1.58

Figure 2

Item characteristic curves for Exposure.2 (top) and Motivation.2 (bottom).



This item demonstrates a floor effect, where students must have high levels of latent ability to select "*Agree*" or above. Response categories 1 and 5 have the highest probability of being selected, and response category 3 has the lowest probability of being selected by respondents. However, most item response curves indicate consistent levels of probability across all five response categories. Item difficulty and discrimination for E.2 and M.2 can be seen in the item response curves above (Figure 2).

Discussion

This study evaluated the use of the *Exposure* and *Motivation in Microelectronics* instrument for examining students' exposure and motivation in Microelectronics careers. The scales were evaluated in two ways: a) do items in the two scales factor in accordance with the theory? and b) are the items sufficiently sensitive in measuring differences in exposure and motivation of students?

The results of the CFA demonstrated that *Exposure* and *Motivation* scales have a factor structure that is consistent with the original instrument (Dyehouse et al., 2008). The data showed acceptable model fit to the selected CFA model based on multiple sources of evidence, indicating that the items are functioning as intended and the two factors are being measured. Although the RMSEA value is slightly elevated, the model fitting process is a holistic process across all the goodness of fit indices (Brown, 2015), and one index should not be evaluated by itself. Overall, the evidence indicates that all 11 items formed a factor structure across two factors (*Exposure* and *Motivation)* that aligned with the theoretical factor structure with acceptable model fit.

The results of the IRT model indicate all items are sensitive towards differing levels of students' exposure and motivation. A common issue with using Likert scales to measure latent ability is elevated means, where students rate all of their abilities highly. These findings are evidence that the *Exposure* and *Motivation in Microelectronics* instrument can capture a range in students' exposure and motivation related to microelectronics with good levels of variance. The instrument was sensitive to differences in high levels of latent ability after intervention, making a strong argument for using the instrument as a pre-/post-survey. At the same time, one item, focusing on students' exposure to university classes on microelectronics, had lower discrimination values and skewed difficulty parameters. This is not surprising, since students in an introductory level engineering course are less likely to have the multiple exposures needed to be motivated for microelectronics internships. On average, students reported higher motivation than exposure, showing students are motivated to pursue careers in microelectronics but have not had many exposure opportunities. Therefore, workforce development programs are needed to provide students with exposure opportunities to support student motivation in specific areas of microelectronics.

Limitations of the study include the limited variance in sample demographics. Data collection was limited a singular predominately White, large research institution. With the results found, it is unknown how well the scale reflects the motivation and exposure of racially minoritized students. However, the items performed strongly with the original instrument indicating that the factor structure is likely stable. Additionally, the evaluation of the *Motivation* and *Exposure* scales is within the context of an introductory design course therefore the difficulty and discrimination parameters should be evaluated with respect to the sample context. Future research should consider the factor structure when administered to multiple first year programs with oversampling of racially minoritized students.

Conclusion

The federal government continues to invest in workforce development programs and engineering research centers to provide opportunities to develop specialized skills and build connections with public and private employers. In accordance with Social Cognitive Career Theory, these programs aim to increase students' interest in microelectronics through multiple exposure opportunities to increase their motivation to pursue careers related to microelectronics. This study examined the factor structure and sensitivity of the *Exposure and Motivation in Microelectronics* instrument. The findings suggest that this instrument can be used to assess introductory level engineering students' exposure and motivation to pursue microelectronics careers. This study shares an assessment with strong validity evidence that is readily adaptable to differing technical areas. Sharing this instrument is important such that others can utilize this instrument rather than developing a new assessment and performing validity studies for similar workforce development programs. Future research may also consider the reproducibility of these results in a larger sample, as well as the effects of further exposure to microelectronics content for more advanced undergraduate and/or graduate students, and the ultimate correlation with career outcomes in the group of measured students.

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