Design and Testing of a Quantitative Instrument to Evaluate Engineering Research Center Participation

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Introduction

The National Science Foundation's (NSF) Engineering Research Center (ERC) program aims to impact society by developing research and innovation in universities across the country [1]. Awards granted by this program are the highest-funded, single award from the NSF; a total of 75 Research Centers have been funded since the program's inception in 1985 [2]. Each ERC engages in research along with additional core activities that promote industry partnership, engineering workforce development, engineering education research, and diversity, equity and inclusion. ERC programs vary depending on their research focus and funding generation (note: centers funded in 2022 were Generation or Gen-4 ERCs), but each ERC must include opportunities for participants (e.g., faculty, postdoctoral researchers, graduate students, undergraduate students, pre-college educators, and K-12 students) at different education and career stages.

NSF has required ERCs to implement data-driven assessment and evaluation of centers to gauge project progress and overall impact on participants since 2015 [3]. These assessment and evaluation tools are usually developed individually by each ERC, which has resulted in multiple isolated efforts to create similar instruments and protocols. Studies resulting from these efforts have demonstrated the impact of specific ERC educational programming. For example, ERCs offer Research Experiences for Undergraduates (REU), Research Experiences for Teachers (RET), and Young Scholars Program (YSP). Studies of these programs have explored their impact on participants, including attitudinal changes and knowledge acquisition of participating undergraduate students [4-6], overall impact on K-14 participants [7, 8], and engagement, diversity, and content knowledge of high school participants [9, 10]. These efforts provide insights regarding specific scenarios but inconsistencies in approaches have minimized the greater possible impact of center evaluations [11, 12].

Large-scale, cooperative efforts are essential to further innovation and effective practices emerging from such centers [11]. A multi-institutional consortium, The ERC Evaluation Consortium (TEEC), was formed to combat prior shortcomings through the design of easily accessible quantitative and qualitative [13] evaluation instruments shared by all centers. The consortium is composed of ERC education directors, researchers, and evaluators from six NSF-funded ERCs.

This research paper reports on the in-progress validation efforts for the Multi-ERC Instrument Inventory (MERCII) survey designed to assess the perceived impact of participating in an NSF-funded ERC for all who engage in the center. The instrument was designed using multiple rounds of design iterations and pilot tests.

Methods

MERCII Survey

The MERCII survey instrument is a web-based survey created by TEEC. Zhen *et. al.* [3] described the process of designing the instrument and initial validity steps taken. The MERCII survey instrument aims to investigate categories set forth by NSF guidelines to evaluate the effectiveness of a center [3]. The constructs used in the analysis were drawn from categories highlighted by the NSF Guidelines. The survey consists of eight sections: 1) research center affiliation (2 items), 2) understanding of the research center (5 items), 3) impact on skills (24 items), 4) culture of inclusion (20 items), 5) mentorship experience (18 items), 6) program satisfaction (11 items), 7) STEM-related future plans (4 items), and 8) demographic information (7 items). An additional ninth section was designed to capture the unique experiences undertaken by RET participants [13]. MERCII survey has gone through a number of iterations in an effort to create a set of tools applicable for all [11].

Sections 2 through 6 of the survey were analyzed for this study. These sections consisted of Likert-type questions with the following scale: not at all =1; very little = 2; somewhat = 3; quite a bit = 4; a great deal = 5.

Data Collection

The instrument was administered to six ERCs between Summer 2021 and Spring 2022. The instrument was shared with center education directors and evaluators so they could individually administer the survey to their members and program participants. Two ERCs did not use the whole instrument. Centers shared their de-identified data with TEEC following implementation. A total of 549 responses were collected. The final dataset consisted of 531 responses after removing blank responses. Response rates were not provided by the partner ERCs.

Demographic data (Table 1) revealed 53.5% of the respondents identified as men, 32.2% as women, and 1.1% as non-binary. A total of 39.5% of the participants identified as White, 23.2% as Asian, 18.6% as Hispanic or Latino/a/x, 7.3% as Black or African American, 0.9% as American Indian, Native American, or Alaska Native, and 0.8% as Native Hawaiian or Other Pacific Islander.

Data Analysis

Variable response to the instrument scales led the team to group items into three categories (Table 2): 1) common, 2) culture of inclusion, and 3) mentorship. Common items referred to the set of items that was used by all participating ERCs without any alteration of the items. Culture of inclusion and mentorship items were sets of items that were used by only a subset of the participating ERCs, which resulted in a varying number of responses. Centers that did not use the culture of inclusion or mentorship items still assessed these categories, but used surveys and/or items used in previous year evaluations for consistency. Each category was analyzed separately using IBM SPSS Statistics 28. The categories all satisfied the recommended data size ratio of five responses per item [14].

Table 1. Demographic information

Gender Identity	N	%
Man	284	53.5
Women	171	32.2
Non-binary	6	1.1
Prefer not to answer	26	4.9
Blank	44	8.3
Total	531	100
Racial/Ethinical Identity	**N**	**%**
White	210	39.6
Asian	123	23.2
Hispanic/Latino/a/x	99	18.6
Black or African American	39	7.3
American Indian, Native American, or Alaska Native	5	0.9
Native Hawaiian or Other Pacific Islander	4	0.8
Prefer not to answer/blank	51	9.6
Total	531	100

Table 2. Survey categories.

Item Category	# of items	# of responses
Common	43	517
Culture of Inclusion	20	333
Mentorship	17	162

The three sets of data were first tested for normality. Skewness and kurtosis were evaluated for normality using a threshold of +/- 2 for skewness and +/- 7 for kurtosis [15]. All common and culture of inclusion items met these criteria. Most mentorship items did not meet these criteria, but analysis continued since this was the first evaluation of these items.

Kaiser-Meyer-Olkin (KMO) and Bartlett's tests were conducted to determine sample adequacy for all subsets of data [16]. The KMO measure was 0.760, 0.965, and 0.923, for the common items, culture of inclusion items, and mentorship items, respectively. These values met the minimum threshold of 0.60 to assess sample adequacy. Bartlett's test of sphericity was significant for all datasets ($p < 0.001$), indicating a sufficient correlation between variables to proceed with the analyses.

We used an exploratory factor analysis (EFA) approach to investigate the underlying structure of the measured items [15]. This statistical method is frequently used to optimize instruments by eliminating statistically ambiguous items and grouping variables in latent constructs. According to Brown [17] and Howard [18], the EFA procedure can be divided into: a) choosing a factor extraction method, b) determining the number of factors to extract, c) choosing a factor rotation method, d) running the factor analysis, e) interpreting the factors and evaluating the quality of the solution, and f) re-running the factor analysis until a final solution satisfying all loading requirements has been obtained.

We used a Principal Axis Factoring extraction method recommended when the objective reveals latent constructs and a relationship among measured variables [19, 20]. A Scree plot and parallel analysis were performed to determine the number of factors [18]. The solutions were rotated using an oblique rotation (Promax), since the approach considers the possible correlations among factors and can be used even if factors do not correlate with each other [21]. Items that had loadings at or below a threshold of 0.32 and those that presented cross-loading values above 0.32 were removed from the analysis [18]. Internal reliability was investigated using Cronbach's alpha [22, 23].

Results & Discussion

The results and discussion break down emergent factors and suggested revisions for the instrument as a result of our EFA analysis. Analysis focused on using the data to better understand how the items were being interpreted and their suitability within the instrument. All survey sections analyzed in this paper had items suggested for removal and/or recommended for modification.

Common Items

The analysis of common items resulted in 29 items (Table 3). Four factors were identified as suitable to extract from both the Scree plot and the parallel analysis. The first factor grouped items that were designed to assess participants' understanding of the ERC and was labeled as *General Understanding*. General Understanding of the ERC consisted of five items with a high level of internal consistency ($\alpha = 0.869$). The second factor, *Impact on Professional Skills*, grouped items related to ERC participation impacting professional skills (e.g., collaborating with others or taking on leadership roles). Professional Skills development in the ERC consisted of six items with a high level of internal consistency ($\alpha = 0.933$). The third factor, labeled *Impact on Research Skills*, grouped items related to ERC participation impacting research performance (e.g. working in a research team or practicing lab safety). Research Skills development in the ERC consisted of eleven items with a high level of internal consistency ($\alpha = 0.941$). The final factor captured *Participants Satisfaction*. Program Satisfaction in the ERC consisted of three items with a high level of internal consistency ($\alpha = 0.883$).

Table 3. Factor structure and factor loadings for common items

Items	Factor			
	Imapct Research Skills	ERC General Understanding	Impact Professional skills	Participation Satisfaction
Working on a research team	0.501			
Managing time efficiently	0.588			
Formulating research questions	0.684			
Analyzing research data	0.934			
Interpreting research results	0.922			
Using research-related tools	0.918			
Making connections between classroom learning and research	0.693			
Conducting research independently	0.819			
Conducting research in an ethical and responsible manner	0.866			
Making connections between existing literature and research	0.879			
Practicing general lab safety	0.659			
Practicing secure data management	0.689			
The mission of [field-ERC]		0.804		
Concepts associated with [field-ERC] field(s) of study		0.783		
How [field-ERC]-specific research helps people address real world issues		0.730		
Which problems are addressed by [field-ERC]		0.803		
Potential career pathway(s) associated with [field-ERC] specific field(s) of study		0.613		
Networking across partner universities			0.595	
Networking with industry			0.749	
Collaborating with others			0.437	
Taking on leadership roles			0.603	
Being entrepreneurial			0.817	
Being innovative			0.616	
I am satisfied with my ERC experience				0.736
I would continue working with ERC if given the opportunity				0.818
I would recommend working with ERC to others				0.978

Data pertaining to some items designed to capture participants' skills suggested the items were written in such a way that hindered their intended interpretation. For example, the items "analyzing research data," "interpreting research results," and "solving research-related problems" were highly correlated with one another. The suggested change for this set of items is to remove "solving research-related problems" and removing "research" from the remaining items to support a more accurate description of participants' experiences. The suggestion was based on the fact that although participants engage in research, they may have other types of professional experiences (e.g., analyzing non-research data). Removing "research" from those items would make it possible to assess participants' experiences more broadly.

Three items were also initially removed because they did not meet the 0.32 factor loading threshold. These items were broadly designed to assess the impact of the ERC on skills like verbal and written communication. These items were rewritten to streamline the number of items addressing this skillset. The new version of the items will be further tested in future iterations and use of the instrument.

Finally, a group of items designed to assess the impact of ERC participation on data collection and data analysis skills were revisited. The first suggestion was the deletion of one item that aimed to evaluate the development of participants' capacity for collecting data and answering research questions. This modification was linked to another discussion around a high correlation between "interpreting research data" and "analyzing research data." The phenomenon could be explained by the proximity between these research steps and the inability to separate each from one another.

Culture of Inclusion

The culture of inclusion data resulted in 17 items (Table 4). Two factors were identified from the Scree plot and parallel analysis. The first factor was interpreted as the way participants *believe the ERC was inclusive.* The construct consists of seven items with a high level of internal consistency ($\alpha = 0.953$). The second factor was interpreted as the way participants *feel the ERC is inclusive*. The construct included seven items with a high level of internal consistency ($\alpha = 0.953$).

Many items designed to capture culture of inclusion revealed high correlations with one another. For example, the item "I believe [ERC] actively promotes diversity" was highly correlated with "I believe [ERC] actively promotes inclusion" and "I believe [ERC] actively promotes equity." The following items were removed to reduce these high correlations: "I believe [ERC] supports participation from members of groups traditionally underrepresented in STEM," "I believe [ERC] is an inclusive place for groups traditionally underrepresented in STEM," "My voice is heard by other [ERC] members," and "I feel welcomed by other [ERC] members."

The high number of items demonstrating high correlations with one another led the team to further examine the appropriateness of items that aimed to understand the experiences of traditionally marginalized groups. A potential confounding issue emerged when allowing majority participants to bias interpretations of structure when having never experienced aggressions against marginalized groups. Results may cover the reality and delay changes are having toward a culture of inclusion. It was also believed that high correlations resulted due to a lack of conceptual understanding for diversity, inclusion, and equity. Some items were retained following EFA because an opportunity exists to longitudinally assess whether participant perceptions of diversity, inclusion, and equity evolve over time, which could result in a reduction of these high correlations.

Table 4. Factor structure and factor loadings for culture of inclusion items

Items	Factor	
	Believe	Feel
Actively promotes diversity	0.913	
Actively advances inclusion	0.886	
Actively creates equity	0.893	
Has a culture that accepts people with diverse perspectives	0.889	
Develops its members to supoprt inclusive practices	0.901	
Provides opportunities to work with and learn from other with diverse perspectives	0.749	
Supports participation from members of groups traditionally underrepresented in STEM	0.850	
Is an inclusive place for groups traditionally underrepresenteded in STEM	0.846	
Enables individuals to contribute to their full potential	0.665	
Is a safe environment for all	0.659	
I have seen others like me succeed in the ERC		0.509
I belong in the ERC		0.846
I am treated fairly as an ERC member		0.73
My contributions are valued by other ERC members		0.953
My life experiences are valued by other ERC members		0.836
My voice is heard by other ERC members		0.926
Welcomed by other ERC members		0.793
Accepted by other ERC members		0.801
Respected by other ERC members		0.803
I am given equal opportunities to fully participate in ERC activities		0.656

Mentorship

Data pertaining to mentorship resulted in 17 items (Table 5). Two factors were identified: *mentorship received* and *mentor performance*. The mentorship received factor consisted of seven items with a high level of internal consistency ($\alpha = 0.911$). The mentor performance factor consisted of nine items with a high level of internal consistency ($\alpha = 0.923$).

Only one issue appeared during the analysis of the mentorship items. The item "advised on my research goals" was further examined to better understand the typical role of an ERC mentor. Participants, especially summer participants, tend to participate in existing research projects. These projects already have set goals and do not require research assistants to develop their own research questions. This item was removed to better capture the experiences of participants in the ERC.

Table 5. Factor structure and factor loadings for mentorship items

Item	Factor	
	Mentor Performance	Receiving Mentorship
Demonstrated knowledge and expertise	0.359	
Helped me further my career goals	0.521	
Served as a role model	0.594	
Demonstrated respectful workplace behavior	0.596	
Established a relationship with me based on trust	0.855	
Encouraged my professional development	0.757	
Cared about me as a person	0.835	
Advocated for me	0.968	
Challenged me to extend my abilities	0.642	
Advices that supports my future plans		0.736
Direction on my research project		0.778
support in conducting independent work		0.789
Feedback that is constructive		0.861
Encouraged to strive for success		0.670
Inspiration to pursue a career in a STEM-related field		0.660
Support to develop my professional network		0.628

Conclusions & Future Work

The presented preliminary findings and discussion provide validity evidence for the MERCII Survey and is intended to further the use of the tool within ERCs and beyond to other similarly structured, large STEM research centers. The instrument is designed to assess the perceived impact of participating in such centers. The in-progress validation process has provided insightful reflections on multiple items regarding the way the items were written, their appropriateness, and their alignment with participants' experiences. This work improves consistency in how ERCs evaluate the effectiveness of their education and diversity programming.

Next steps will involve further distribution of the instrument and increasing its use among interested centers to further the validity evaluation of the instrument. It is expected that this instrument will facilitate greater cooperation between ERCs and other large, STEM research centers. Our future work will continue to gather validity evidence for the use of this instrument in evaluating efforts across ERCs and the predictive validity of these outcomes on preparing the future engineering workforce. The next steps of this project will consist in the launch of our online platform which will host the MERCII Survey as well as other instruments designed by TEEC.

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