Development and Impact of Research Efficacy in a Undergraduate Teaching-Assistant Certification Class

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1. Introduction

Research experiences and opportunities are growing in availability and significance for undergraduate students. Furthermore, undergraduate students can offer a distinct perspective and a unique form of assistance compared to graduate students and faculty. This also applies to the classroom. Participation in research in the undergraduate years, shows to provide all engineering student populations (including marginalized groups) to consider a job in the academic and research fields.

At a mid-size minority serving institution, undergraduate students are highly encouraged to participate in research whether it be a lab on campus or external experiences. Furthermore, undergraduate students are offered the opportunity to serve as teaching assistants (termed as teaching fellow) in several undergraduate classes. This program was developed at University of Maryland, Baltimore County (UMBC) in 2013 in two engineering departments and expanded to the entire College of Engineering and Information Technology (COEIT) in 2017. In 2022, due to their practitioner experiences, these students were offered to participate in earning a certification in Scholarship of Teaching, Research and Learning from the Center for the Integration of Research, Teaching and Learning (CIRTL), a nationally recognized program.

To obtain the certification, students are required to engage in two seminar classes: Seminar One, covering the Fundamentals of Teaching Fellow Scholarship (Engineering 396 - ENES 396) and Seminar Two, Engineering 397 (ENES 397), which delves into Advanced Topics of Teaching Fellow Scholarship. In Seminar One, the primary focus is on instructing students about research and learning essentials while aiding them in shaping their teaching philosophy. In Seminar Two, students are challenged to participate in more advanced workshops and concentrate on the development, creation, and execution of a teaching action research project.

This research, a continuation from previous assessments and studies [1], centers on the second seminar class and investigates the research efficacy of two cohorts of students who have successfully completed both seminar classes. The evaluation focuses on their confidence to guide and navigate research within the realm of engineering and computer science education, with a specific emphasis on aspects such as idea generation, research implementation, and presentation of findings.

2. Background

Elevating the engagement of undergraduate students in research is becoming progressively essential. This is evident in initiatives such as the Research Experiences for Undergraduates program funded by the NSF. At our R1 minority institution, it is both a mission and a priority to offer such opportunities to our students. Investments in programs like the Undergraduate Research Awards (URA) and Undergraduate Research and Creative Day (URCAD) enable students to explore and comprehend the essence of research.

Undergraduate students participating in research experiences show to enhance many of their technical and professional skills [2], [3]. Communication and critical thinking, career clarification and even further aspirations to continue to graduate school have been documented because of a research experience for a student [2], [4], [5]. Another key and important element, especially at UMBC, is the impact on diversity. These experiences demonstrate increasing self-efficacy in students who are working to complete a STEM degree, especially women and marginalized populations [5], [6], [7], [8].

However, not all students have the chance or find themselves in a position to pursue such an opportunity. Also, many STEM undergraduates haven't considered the option to pursue research in education. CIRTL's focus on students understanding the best practices of scholarship of teaching and learning. UMBC has been a member since 2016. Although strictly for graduate students, UMBC made the case to offer the program to undergraduate students due to their long involvement with using undergraduates in the classroom (aka. Teaching fellows) and the long-standing commitment to undergraduate research.

To attain an Undergraduate Associate Certificate from CIRTL, students are required to serve as active teaching fellows during their enrollment in Engineering 397 and successfully complete both seminar courses with a passing grade of P.

The following section covers the courses with special emphasis on the second seminar course.

2.1. Course Structure

2.1.1. First Seminar Course: Engineering 396 (ENES 396): Fundamentals of Teaching Fellow Scholarship

This first course is designed to enrich undergraduate teaching assistant knowledge and understanding of the scholarly practices of teaching, learning and research. Throughout the semester, students attend workshops and seminars that focus on the researched and applied best practices in the field of Engineering and Computing education. Further, teaching fellows are encouraged to develop a teaching philosophy. As topics are introduced, the instructors encourage students in both discussion and thoughtful development of how this applies to their own teaching practice. Students also engage in various fundamental workshops and seminars in Engineering and Computing Education not limited to Scholarship of teaching and learning, Cultural Awareness and Diversity, Equity, and Inclusion. Gurganus and Berczynski investigated the impact of this first course and continue to expand on this research [1].

2.1.2. Second Seminar Course: Engineering 397 (ENES 397): Advanced Topics of Teaching Fellow Scholarship

Furthering the knowledge and comprehension of engineering and computational learning, Teaching Assistants in the realms of teaching, learning, and research, participants engaged in various workshops and seminars centered on the latest and most effective practices in Engineering and Computing education.

Since this course is primarily hands-on, students take on the role of peer advisors for new students in the first seminar course. They actively participate in guiding and fostering advanced learning and research in Engineering and Computing Education. These students are anticipated to delve into more complex subjects related to teaching, research, and learning. The topics covered in Engineering 397 encompassed the following (but not limited to), Completing a Research project related to a topic around Scholarship, Research, Teaching and Learning (SoTL), Peer Mentoring and Team lead and facilitating one of the first seminar discussions/lectures.

In a more hands-on approach, students in this course act as peer advisors to incoming 396 students, fostering higher-level learning and research within Engineering and Computing Education. These individuals are anticipated to engage in advanced discussions on teaching methodologies, research practices, and learning strategies.

Topics covered in Engineering 397 included the following:

- Completing a Research project related to a topic around the Scholarship of Teaching research and learning with the intent of presenting at a conference. As shown in the picture below (Figure 1), students presented their research at the end of the semester to both their peers in ENES 396 (mentoring model) and to the Dean and Associate Vice Provost for Graduate School, the National Director for the Center for the Integration of Research, Teaching and Learning, affiliate and mentor faculty and instructors. They also presented at the Provost Teaching and Learning Symposium as shown in Figure 2.
- Attending two advanced workshops with Faculty at the home institution
- Peer Mentoring: Students will mentor their ENES 396 peers and provide evaluation on their teaching practices and facilitation throughout the semester. This includes them attending one lecture/discussion of their peers.
- Team lead and facilitate one ENES 396 discussion/lecture. Students will plan and facilitate a topic in ENES 396 or in their own classrooms that will be approved by the instructor.

After completing ENES 397 and a research project, students earn undergraduate CIRTL associate certification.

Figure 1. ENES 397 graduation cohort 1


Figure 2. ENES 397 graduation cohort 2

2.2. Research Topic Examples

Students have an opportunity to choose their research topic and their partners. We encourage them to form groups of three to five students. After formulating their research groups, they work with the instructor to come up with a research question. Projects have included implementation of interventions, examining data, designing new ways of learning and more. Below are two sample abstracts from students in engineering and computing disciplines. The engineering project focuses on creating a game that would help students understand how socioeconomic status impacts academic achievement. The computing project focuses on a first-year course, Computing 101, facilitating a new communication technique that helps monitor and engage students in their well-being and any challenges that normally would not be noticed.

2.2.1. Sample Engineering Research Abstract

Effects of Socioeconomic Status on Academic Performance of UMBC Engineering Students

Research has indicated that socioeconomic status is a predictor of academic performance, with lower socioeconomic status being linked to lower academic achievement and slower rates of learning progress. This paper analyzes how socioeconomic status may play a role in the academic performance of UMBC engineering students. To perform this analysis, students will be selected to participate in a game which randomly assigns students to a specific social class, ranging between high and low, representing the family/socioeconomic class they are born into, allowing them to start with either extra funds or advantages in the game. During the game the students will have a chance to earn more money, representing having a job and earning money before starting university. The student that ends with the most money wins the game. It may be apparent throughout the game that some students were given a clear advantage, whereas other students either never climbed higher or had a very hard time climbing higher. At the end of the game the students will be allowed to spend the money they earned in the game for random items that may later be used in a quiz. These items could include use of their laptops, notes, extra time, candy, etc during the quiz. The students will not be told the items will be used for the quiz until after they purchase. They will also be allowed to work together, but will not be told that they can. The students will then be given a short exit poll about the experience. This research will provide valuable data on how socioeconomic status affects academic performance by allowing the research team to observe the behavior of the students and take notes during the games progress, as well as scoring the quizzes and analyzing the exit poll data. Our hypothesis is that the students that start at a higher class, receiving more funding, will score better on the quiz, have an easier time during the game and give a more positive exit poll review, while the students who are starting as the low class will struggle throughout the experience. This research can provide evidence-based data to show the advantages and disadvantages of socioeconomic status during a student's time at university.

2.2.2. Sample Computing Abstract

Enhancing Student Progress through Effective Communication and Regular Check-Ins in Computing 101

In today's rapidly evolving educational landscape, fostering effective communication among students is key to their success and overall development in classes. This topic explores the strategies and methodologies drawn upon to meet students' needs with projects, actively track their progress, and witness the transformative effects of improved communication within student groups.

This study will delve into the critical role that communication plays in promoting academic and personal growth. We will discuss various techniques and tools used to facilitate communication between students, including digital platforms, collaborative projects, and peer learning. By creating a nurturing environment that encourages open dialogue and information sharing, we aim to empower students to become more engaged and proactive learners. Furthermore, we will emphasize the importance of regular check-ups and daily check-ins as essential components of our approach. These check-ins serve as touchpoints for monitoring students' well-being, addressing any challenges they may face, and providing timely support. We will also try to gain a grasp of how well the other team members are performing and if there should be any concerns so we can prevent any last minute issues. We will also analyze this semester's team assessment surveys in comparison to those from the previous semester to determine whether the implementation of guided check-ins has led to an overall improvement in team members' satisfaction.

3. Methodology

3.1. Dissemination of the Research Self-Efficacy Scale (RSES)

Participants who completed both seminar classes (defined as Cohorts) were encouraged to fill out the Research Self-efficacy Scale (RSES) [9] via email.

The Research Self-Efficacy Scale (RSES) consists of 49 items. Based on the used items' response format (11-point Likert-scale with the anchors 1= no confidence, 6= moderate confidence, and 11 = complete confidence) higher scale values imply higher values of self-efficacy. A principal component analysis (PCA) showed that these items build four sub-scales, (i) *Conceptualization*, (ii) *Implementation*, (iii) *Early Tasks*, and (iv) *Presenting the Results*, explain 57 % of the RSES' variance. *Conceptualization* (16 items) covers fundamental stages of organizing and synthesizing knowledge and ideas for research topics. The sub-scale showed an internal consistency of Cronbach's $\alpha = .92$. With a Cronbach's $\alpha = .96$, *Implementation* (20 items) represents practical tasks needed to perform an empirical research project, e.g., performing experiments, collect and process data, or statistical analysis. In the dimension *Early Tasks* (5 items, Cronbach's $\alpha = .75$) represents considering ethical principles and performing literature research in databases and libraries. *Presenting the Results* (8 items, Cronbach's $\alpha = .91$) covers tasks to communicate research results in various forms. [9]

3.2. Demographics

In total $N = 19$ UMBC students from College of Engineering and Information Technology (COEIT) responded to the survey between two different cohorts. The first cohort *graduation-spring-23* consists of $n = 11$ participants, the second one *graduation-fall-23* of $n = 8$. Details regarding the participants' major, gender, and ethnicity across the two cohorts are shown in Table 1.

Table 1
Demographics of participants

		Cohort	
		graduation-spring-23	graduation-fall-23
Major	Mechanical Engineering	4 (36.4 %)	5 (62.5 %)
	Computer Science	4 (36.4 %)	3 (37.5 %)
	Chemical Science	3 (27.3 %)	0
Gender	Male	7 (63.6 %)	6 (75 %)
	Female	4 (36.4 %)	1 (12.5 %)
	Gender fluid/queer	0	1 (12.5 %)
Ethnicity	African/Black American	2 (18.2 %)	1 (12.5 %)
	Asian & Pacific American	2 (18.2 %)	3 (37.5 %)
	White American	6 (54.5 %)	2 (25 %)
	Asian & Pacific + White American	1 (9.1 %)	2 (25 %)

Note. Values show absolute frequencies, values in brackets relative frequencies related to sub-sample size.

4. Results

4.1. Data Analysis

Statistical analyses in this contribution were performed in SPSS [10], jamovi [11] and R [12]. In general, robust approaches of inferential statistical analyses were performed, preventing inflation of type-1-error-rate or loss of test-power, although data might be non-normal distributed or compared groups show unequal variances.

4.2. Item analysis to validate survey with new sample

4.2.1. Item-difficulties

The item-difficulty $P(i)$ of an item i is a numerical value between 0 and 1 that indicates the probability of agreeing or disagreeing with the statement of the item i. Therefore, an item-difficulty of $P = 0.5$ shows the highest variability in response behavior. The performance of items with difficulties below 0.2 or above 0.8 is usually not sufficient to differentiate between participants [13], [14]. Table 2 gives an overview across the item-difficulties of the four sub-scales of the RSES. In result, 23 of the 49 items show item-difficulties above the upper threshold. In these items the participants showed very high ratings in self-efficacy.

Table 2
Sub-scale item-difficulties statistics

Sub-scale	Item-difficulty rating: Number of items…			*Min P(i)*	*Max P(i)*	*M P(i)*	*SD P(i)*	*Md P(i)*
	below range	in range	above range					
Conceptualization	0	7	9	.52	.95	.78	.11	.82
Implementation	0	11	9	.59	.92	.79	.09	.79
Early Tasks	0	3	2	.66	.90	.77	.10	.78
Preset. the Results	0	5	3	.59	.87	.75	.10	.74

Note. Min P(i) = minimum of item-difficulty range. *Max P(i)* = maximum of item-difficulty range. *M P(i)* = mean of item-difficulty. *SD P(i)* = standard deviation of item-difficulty. *Md P(i)* = median of item-difficulty.

4.2.2. Corrected item-total correlations

The part-whole-corrected item-total correlation *r(i,total-i)* of an item *i* indicates how much the item *i* measures the same psychological construct as the other items combined *(total-i)*. Values between 0.4 and 0.7 are preferred [14]. Table 3 gives an overview of item-total correlations of the 49 items taking the four sub-scales as well as the aggregated total scale into account.

Table 3
Corrected item-total correlation for sub-scale and total RSES value

(Sub-)Scale	*r(i,total-i)* rating: Number of items…			*M*	*SD*	*Min*	*Max*
	below range	in range	above range				
Conceptualization	7	7	2	.44	.24	.09	.78
Implementation	10	6	4	.42	.27	-.18	.74
Early Tasks	1	1	3	.54	.42	-.19	.83
Preset. the Results	3	3	2	.52	.25	.13	.83
Total RSES	22	14	13	.44	.30	-.21	.86

Note. r(i,total-i) = part-whole-corrected item-total correlation. *M* = mean of *r(i,total-i)*. *SD* = standard deviation of *r(i,total-i)*. *Min* = minimum of *r(i,total-i)*. *Max* = maximum of *r(i,total-i)*.

From the sub-scale perspective as well as from the perspective of the total RSES score multiple items do not show item-total-correlations within the preferred value range. Particularly noteworthy are the items that correlate very low or even negatively with the associated scale, as this may indicate that the items-dimension-structure deviates from the in [9] reported one.

4.3. RSES-Scale Assessments

Table 4 shows the results of the scale analyses of the four subscales as well as the total RSES scale. The analysis contains the descriptive values of the participants responses across both cohorts, the Pearson’s product-moment-correlation between the four subscales as well as the total scale, and related (sub-)scale reliabilities.

Table 4

(Sub-)scales' descriptive values, inter-scale correlations, and reliabilities

Sub-scale	**Group**	***n***	***M***	***SD***	***Md***	***Min***	***Max***	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
(1) Conceptualization	Total	19	8.80	0.94	8.88	6.63	11.00					
	Cohort 1	11	9.10	1.03	9.19	6.63	11.00	(.83)				
	Cohort 2	8	8.39	0.64	8.63	7.31	8.94					
(2) Implementation	Total	19	8.93	0.83	8.75	7.75	10.45					
	Cohort 1	11	9.22	0.85	9.25	8.05	10.45	$.72^{***}$	(.80)			
	Cohort 2	8	8.52	0.62	8.60	7.75	9.50					
(3) Early Tasks	Total	19	8.75	1.66	8.60	3.00	11.00					
	Cohort 1	11	8.91	2.19	9.20	3.00	11.00	$.73^{***}$	$.46^{*}$	(.79)		
	Cohort 2	8	8.53	0.38	8.40	8.20	9.40					
(4) Preset. the Results	Total	19	8.54	1.30	8.75	5.38	10.38					
	Cohort 1	11	8.67	1.30	8.88	5.38	10.25	$.67^{**}$	$.54^{*}$	$.54^{*}$	(.80)	
	Cohort 2	8	8.36	1.37	7.88	6.88	10.38					
(5) Total RSES	Total	19	8.80	0.87	8.84	6.71	10.53					
	Cohort 1	11	9.06	0.99	9.31	6.71	10.53	$.93^{***}$	$.86^{***}$	$.76^{***}$	$.79^{***}$	$(.92)^{***}$
	Cohort 2	8	8.45	0.55	8.53	7.67	9.14					

Note. n = sample size. M = mean, SD = standard deviation. values in brackets show sub-scales' reliability in Cronbach's Alpha.
values below diagonal show Pearson's product moment correlation. * $p < .05$, ** $p < .01$, *** $p < .001$

The observed (sub-)scale reliabilities exceed the desired minimum value of .7 [13], [14] and match the reported scale consistencies in [9]. The sub-scales correlate with each other as well as with the total scale significantly. According to [15], the correlations can be classified as large.

4.4. Analysis of group differences between cohorts

Based on the small sample size, expected non-normal distribution in the dependent variables, and unequal group-sizes, respectively non-exchangeability between the compared groups, the comparison between cohort 1 and cohort 2 were performed by a Brunner-Munzel test in jamovi [16]. The BM-test were performed with full permutation approach [16], [17] and two-tailed.

Cohort 1 tends to show higher research self-efficacy values in the dimension *Conceptualization* (BM_{fp} = -2.80, p = .023) and dimension *Implementation* (BM_{fp} = -2.28, p = .048). Splitting ties equally, the probability that a random cohort 1 participant shows less *Conceptualization Self-Efficacy* than a random cohort 2 participant is $\hat{p}$ = 20 %, respectively $\hat{p}$ = 24 % for showing less *Implementation Self-Efficacy*. Regarding dimension *Early Tasks* (BM_{fp} = -1.47, p = .160) and *Presenting the Results* (BM_{fp} = -0.43, p = .660) the self-efficacy values of both cohorts were comparable. Splitting ties equally, the probability that a random cohort 1 participant shows less *Early Tasks Self-Efficacy* than a random cohort 2 participant is $\hat{p}$ = 30 %, respectively $\hat{p}$ = 43 % that a random cohort 1 participant shows less *Presenting the Results Self-Efficacy*. As a result, both cohorts show no significant deviation regarding the total *Research Self-Efficacy Scale* (BM_{fp} = -2.12, p = .059). The probability that a random cohort 1 participant shows less Research Self-Efficacy than a random cohort 2 participant is $\hat{p}$ = 25 %, splitting ties evenly. Figure 3 shows raincloud-plots of the RSES total values of both cohorts.

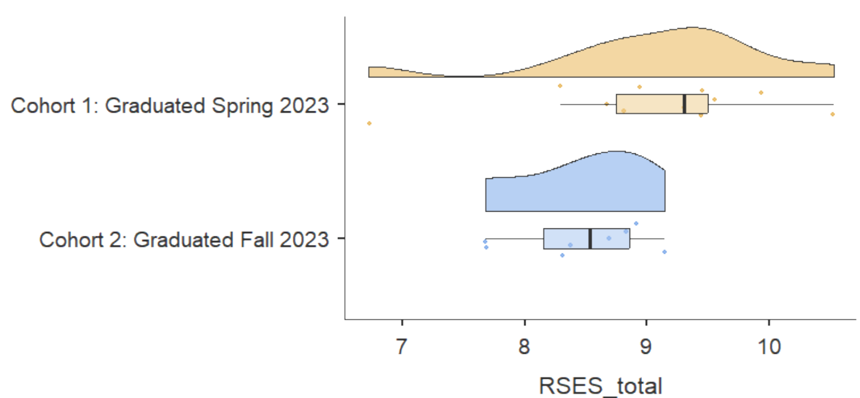

Figure 3. Cohort-comparison of RSES total value

5. Discussion and ongoing work

Both groups demonstrated a high positive research efficacy at the end of completing their certificate. Cohort 1 showed a significantly greater confidence especially in *Conceptualization* and *Implementation* compared to Cohort 2. However, as shown in the data there is only a 76 % to

80 % probability you will find higher values in a random cohort 1 participant. In *Early Tasks* and *Presenting the Results* both cohorts were equally strong. Unfortunately, as a limitation of this study, pre-measurements were not taking to provide a comprehensive assessment of the gain in research.

Presently, with Cohort 3, we are in the process of conducting pre-measurements utilizing the RSES. This endeavor aims to offer a longitudinal understanding of whether this model has effectively supported and increased the efficacy research within engineering and computing education.

***Special Acknowledgements** to Mark Berczynski Co- Instructor and developer for both seminar classes.*

Resources

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