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Work-In-Progress: Continued evaluation of engineering self-efficacy and judgement for an artificial intelligence, modeling, and simulations (AIMS) certificate program

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Introduction

Humans have a long history of striving to better understand the natural world. The knowledge accumulated is then frequently leveraged to develop new ideas yet to be tested and new mechanisms for the benefit of human welfare. Humans accomplish extraordinary feats but solving today's complex problems require specialized learning and time. In the modern world, these types of problems are increasingly common and solving them quickly is becoming increasingly important [1]. Artificial intelligence (AI) has been increasingly utilized to tackle this ever-growing issue due to its ability learn and classify complex data. AI can be described as two main subfields: machine learning (ML) and deep learning (DL). ML leverages labeled data to build models for predicting labels on unlabeled data. DL relies on extensive unlabeled datasets to uncover underlying patterns within the dataset. On the other hand, knowledge-based modeling and simulation (M&S) techniques utilize known models to generate data for the analysis of new and existing designs. M&S works well for simple systems but becomes increasingly difficult for more complex systems. The difficulty comes from the uncertainties associated with each added variable being modeled. To bridge the gap between AI and M&S, the Mechanical Engineering Department at the University of Iowa created an artificial intelligence, modeling, and simulations (AIMS) certificate in partnership with the U.S. Department of Education designed for both graduate and undergraduate students. Undergraduates receive exposure to state-of-the-art technology and techniques used in industry to help prepare them for their future careers. Graduates learn cutting edge methods which will help drive to success in research and contribute to their respective communities.

The AIMS certificate was specifically designed for undergraduate and graduate students in the Mechanical Engineering Department, though students in other engineering subdisciplines as well as anyone in a related field outside of the College of Engineering can pursue it. The certificate offers a range of course options with the ability to petition to substitute relevant courses offered in other departments provided they align with the certificate's goals. The undergraduate certificate requires 18 semester hours of coursework, or 6 classes, while maintaining above a 2.00 GPA. The graduate certificate requires 15 semester hours, or 5 classes, while maintaining above a 3.00 GPA. The goals of the AIMS certificate are for students to learn reliable computer simulation and design under uncertainty, gain an understanding of the new pathways to achieve robust and affordable modeling with artificial intelligence and machine learning, and become proficient in utilizing hybrid models toward intelligent complex machines.

Many of the AIMS courses provide hands-on projects designed to aid students in developing a deeper understanding of the material, contributing to improved retention of knowledge gained, and encouraging collaboration amongst students. An example project from the course "Artificial Intelligence in Engineering" presented groups of students with the challenge of identifying general ship types with the use of computer vision and Convolutional Neural Networks (CNN). Students selected ships from an online source to form their dataset on which the CNN was initially trained. The dataset was subsequently expanded through data augmentation, which was used to improve the CNN's accuracy. In this project, students had some freedom in the implementation of the CNN and image selection with the educational benefit of understanding the inherent tradeoffs associated with each of those decisions. Another example project comes from the course "Data Driven Analysis," which provided students with the opportunity to select any topic related to course material. Neural networks (NN) were used throughout the course and many potential projects involved altering the architecture to solve various complex problems. Problem examples included handling a steady-state heat transfer problem, designing a truss system with shifting magnitudes, and inventing novel algorithms for use in a neural network. Both classes gave students the opportunity to be creative within their projects and experiment with other variations that piqued their interest.

AIMS courses involve complex problem-solving and application of advanced computation techniques to complete various coursework. By successfully engaging with these topics, students can enhance their confidence and discernment in handling technical challenges. The goal of this work is to explore the effects of AIMS courses on two student constructs: engineering self-efficacy (ESE) and engineering judgement (EJ). ESE is an individual's belief regarding their ability to achieve a specific goal based on their engineering knowledge [2]. Past literature has shown that an individual's ESE has an influence on behavior and goal attainment [2]. Importantly, students with strong ESE are more engaged in course work and find classes to be more useful [3]. ESE is also integral for the entry into engineering programs and the persistence to continue [4]. EJ is an individual's capacity to determine and execute tasks that will have a predicted outcome [5, 6]. When engineers work in the real world, many times projects will require the engineer to come up with solutions which cannot be found inside of codes or manuals. When following a structural engineering firm, the engineers were able to analyze building plans and make changes to designs based on previous knowledge [7]. An engineer may be an expert when using codes and references but cannot be a competent engineer if lacking EJ [8]. During an engineering student's curriculum, EJ should be developed incrementally and purposefully. The scaffolding used to create assignments is important and can cause students to display different judgements during a project based on available materials [9].

This work-in-progress paper investigates the relationship between participation in the AIMS certificate and the two aforementioned constructs (ESE and EJ). Specifically, we are interested in how other factors like academic standing, participation in extracurricular activities, and general interest in the AIMS certificate programs potentially mediate participation in the AIMS certificate programs. This paper opens with a description of the survey, participants, and description of the analysis of data. Preliminary results are presented followed by a discussion, initial conclusions, and future work.

Methods

The goal of this work is to continue investigating the relationship between participation in the AIMS certificate programs and constructs of interest (ESE and EJ). A survey was distributed among students enrolled in 6 core AIMS courses over the past 2 years with recorded responses from 38 graduate students and 98 undergraduate students. Students were asked questions related to ESE [10] and EJ [7] based on the articles referenced. An example question for ESE was “I can do well in an engineering major during the current academic year” and for EJ was “I can determine when a calculation or estimation is good or precise enough”. The levels of agreement for the questions were indicated by a Likert scale (Table 1). Students self-reported participation in AIMS-related workshops and extracurricular activities. Additionally, student interest for the AIMS certificate was categorized ranging from not being interested in the program to actively participating.

Table 1: Likert scale indicating levels of agreement with questions related to ESE and EJ.

Numerical Response	Level of Agreement
(1)	Strongly Disagree
(2)	Disagree
(3)	Somewhat Disagree
(4)	Somewhat Agree
(5)	Agree
(6)	Strongly Agree

Table 2: Likert scale indicating level of interest in the AIMS program.

Numerical Response	AIMS Interest
(1)	No, I'm not interested in applying to AIMS
(2)	I'm not familiar with the AIMS program and I would not like to learn about AIMS
(3)	I'm not familiar with the AIMS program and would like to learn about AIMS
(4)	Yes, I'm interested in applying to AIMS
(5)	I have already applied to AIMS

First, a Pearson correlation coefficient is calculated between the ESE and EJ constructs. A statistically significant correlation is expected, but a correlation greater than 0.85 would indicate that the two constructs are not different enough from one another [11].

Next, t-tests were conducted to determine if there were significant differences in either of the constructs according to academic standing. It is reasonable to expect students who are farther along in their educational journeys to report higher levels of self-efficacy or judgement, though longitudinal assessments of engineering self-efficacy do reveal stagnation in developing those constructs throughout undergraduate engineering programs (e.g., [3, 9]).

Finally, an analysis of variance (ANOVA) was also performed on the student outcome data. The main factors of interest included workshop participation, extracurricular activity participation, and interest in the AIMS program. Example workshops that students may have participated in include Introduction to Python and Career Development, among others. Some extracurricular activities that students may have engaged in include a university-sponsored Hackathon, involvement in engineering student organizations, and other campuswide organizations. We hypothesize that students who go out of their way to participate in additional opportunities like workshops and extracurricular activities might be afforded more occasions to develop their ESE and EJ. Interaction terms were not included for the ANOVA, in part due to the relatively small sample size currently available. The outputs used were the average scores collected for the survey items associated with ESE and EJ, respectively. For an ANOVA with a statistically significant result, Tukey post-hoc tests were conducted to determine which factor groups were significantly different from one another. All statistical tests were evaluated with a significance level of $\alpha = 0.05$.

Results and Discussion

The correlation coefficient between ESE and EJ was determined to be 0.568 which is higher than the previous study coefficient of 0.453 [11]. These values indicate a moderately strong correlation, but not strong enough to render the constructs of ESE and EJ as they were measured by the survey to be effectively the same. In Figure 1, the number of students for each level of AIMS interest are reported. The majority of responses (82) indicated a positive view of the program with few responses (3) of no interest in the program without wanting to learn more. Since the number of students who responded with (2) were so small, they were grouped together with the students who responded with (1) for the sake of statistical significance.

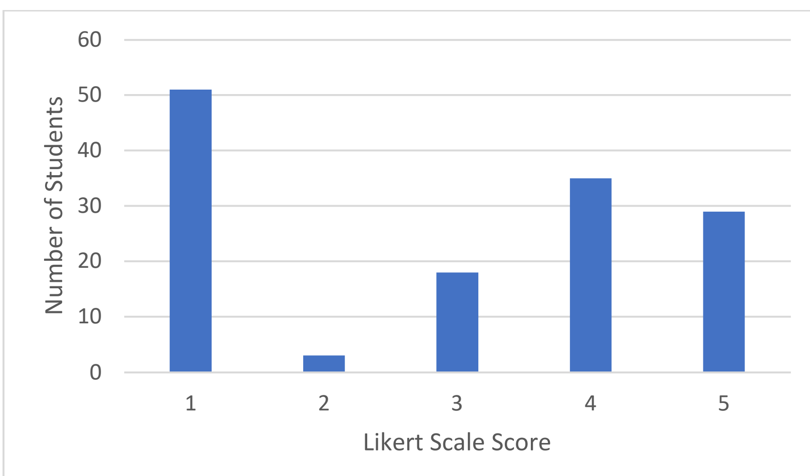

Figure 1: Number of student responses to AIMS interest.

Next, the results of the t-test performed on the ESE and EJ constructs by academic standing are reported in Tables 3 and 4, respectively. In both instances, the p-value were greater than 0.05, which indicates ESE or EJ are not significantly different between undergraduate and graduate students. This result can partially be explained by the fact that many of the graduate students in the mechanical engineering department are engaged in a combined degree program in which they earn a Master's degree in the year following the completion of their Bachelor's degree. Thus, these students might not have significantly more experience than their undergraduate counterparts who are taking the AIMS courses as their advanced technical electives in their final year of their degree program.

Table 3: T-test results for ESE.

	Undergraduate	Graduate
Average	5.27	5.46
STDEV	0.58	0.62
t-stat	-1.58	
P-value	0.12	

Table 4: T-test results for EJ.

	Undergraduate	Graduate
Average	4.68	4.87
STDEV	0.59	0.70
t-stat	-1.53	
P-value	0.13	

Prior to conducting the ANOVAs, the normal distribution and homogeneity of variance assumptions were verified graphically. It is assumed that each student's response is independent of other student's responses since they are given time during the AIMS class to complete the survey individually. The results of the 3-way ANOVAs are reported in Table 5 and Table 6 for ESE and EJ, respectively. The statistical results for both ESE and EJ revealed a statistically significant effect associated the factor "AIMS Interest".

Table 5: ANOVA results for ESE student outcome.

Factor	Sum Sq.	Degrees of Freedom	Mean Square	F-statistic	p-value
Extracurricular	0.15	1	0.15	0.48	0.49
AIMS Interest	4.86	4	1.22	3.78	**<0.01**
Workshop	0.88	1	0.88	2.74	0.10
Error	41.52	129	0.32		
Total	48.04	135			

Table 6: ANOVA results for EJ student outcome.

Factor	Sum Sq.	Degrees of Freedom	Mean Square	F-statistic	p-value
Extracurricular	0.41	1	0.41	1.12	0.29
AIMS Interest	4.97	4	1.24	3.39	**0.01**
Workshop	0.08	1	0.08	0.21	0.65
Error	47.35	129	0.37		
Total	52.90	135			

Given the statistically significant ANOVA results for AIMS interest, Tukey post hoc tests are conducted for that factor to determine which group(s) is(are) significantly different from the rest. Figure 2 and Figure 3 illustrate that groups (1) and (5) are significantly different for ESE and EJ, respectively.

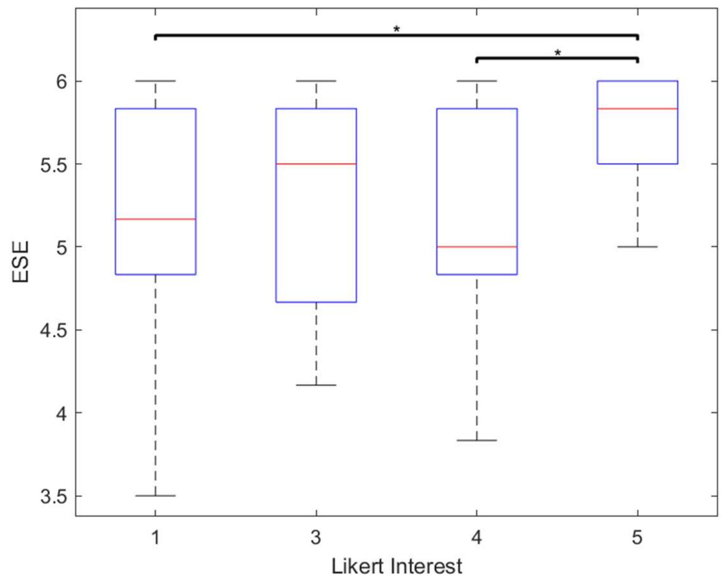

Figure 2: AIMS interest to ESE scores

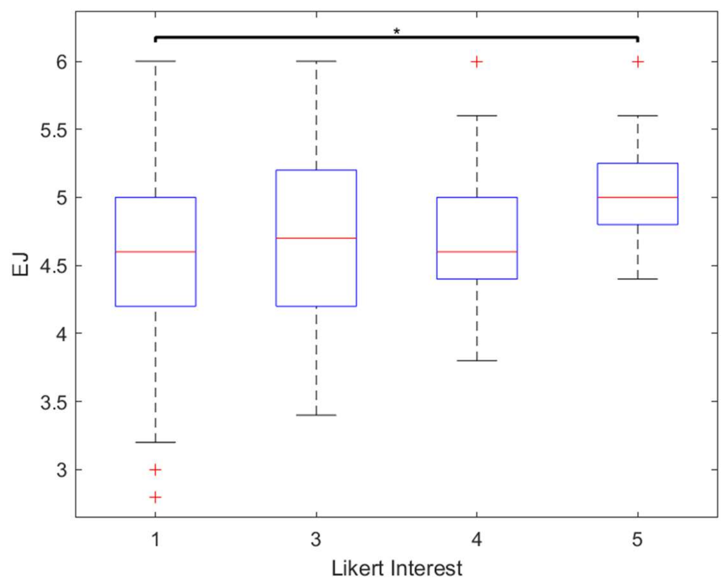

Figure 3: AIMS interest to EJ scores

The statistical results for the post hoc tests are reported in Tables 7-9 for ESE and EJ, respectively. For reference, the interpretation for the magnitudes of the Cohen's *d* effect size are as follows: 1) small > 0.2, 2) medium > 0.5, and 3) large > 0.8 [12].

Table 7: Post-hoc statistical results for groups 1 and 5 for ESE.

	Mean	p-value	Cohen's *d*
Group 1	5.2	<0.01	0.70
Group 5	5.7		

Table 8: Post-hoc statistical results for groups 4 and 5 for ESE.

	Mean	p-value	Cohen's *d*
Group 4	5.2	<0.01	0.72
Group 5	5.7		

Table 9: Post-hoc statistical results for groups 1 and 5 for EJ.

	Mean	p-value	Cohen's *d*
Group 1	4.5	<0.01	0.66
Group 5	5.1		

The post hoc results indicate that AIMS Likert groups 1 and 5 are significantly different for both ESE and EJ as shown in Tables 7 and 9, respectively. Both tables demonstrate p-values below the 0.05 threshold and moderately large effect sizes. These results show students with high levels of AIMS Interest demonstrate higher levels of ESE and EJ than those with no interest. A potential reason behind this trend is due to the AIMS program being a voluntary certificate. Students that perform voluntary actions outside of degree requirements have been shown to have strong ESE and EJ. The analysis also showed groups 4 and 5 are significantly different for ESE as shown in Table 8. This result was somewhat unexpected and could be due to similar reasons as before with one group being in the program (Group 5 – "I have already applied to AIMS") while the other group is not as committed (Group 4 – "Yes, I'm interested in applying to AIMS"). Participation in workshops and extracurricular activities were not shown to have significant effect on ESE and EJ. However, there is still a possibility the factors play a role in ESE and EJ for the students.

Conclusions

The goal of this work was to investigate the relationship between AIMS participation and student constructs, specifically with respect to what factors may affect that relationship. The constructs of interest were engineering self-efficacy (ESE) and engineering judgement (EJ). Other factors considered were workshop participation, academic standing, extracurricular participation, and interest level in the AIMS program. Results from the ANOVA showed that AIMS interest levels had a significant effect on ESE and EJ. Future work will include gathering additional data on students participating in AIMS courses to gain more insight on the average student construct, analyze additional data pertaining to an engineering leadership construct, and collect further information on student participation in other extracurricular activities like a hackathon.

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