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Embedding Artificial Intelligence Algorithms in an Engineering Computational Modeling Course

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Abstract

This abstract for a full paper addresses embedding artificial intelligence (AI) algorithms into an engineering computational modeling course as a continuation of previous work introducing AI concepts into engineering-education [1]. While initial efforts focused primarily on generative AI and machine learning as a means of building early AI literacy, this study expands the scope by integrating practical algorithmic techniques directly into the coursework of a second-year engineering course. The goal was to improve students' comprehension of AI methods, increase their awareness of ethical and practical implications, and evaluate their motivation to seek out further information about AI.

In this implementation, MATLAB™ toolboxes for neural networks and fuzzy logic were introduced alongside conventional modeling approaches. Students applied these AI methods to practical engineering problems, including image processing tasks such as object recognition. One exercise compared the effectiveness of AI-driven image detection techniques with more traditional approaches, such as FOR loops and threshold-based image processing, for identifying an apple. This comparison allowed students to directly evaluate the trade-offs between classical programming and AI-based solutions, highlighting where AI algorithms can provide greater adaptability and efficiency, and where simpler methods may be more appropriate.

To assess student outcomes, a survey instrument was administered both before and after the AI learning modules. The pre-survey established baseline levels of comprehension, awareness of

limitations, and motivation to learn more about AI, while the post-survey expanded this scope to include measures of ethical understanding, recognition of bias, and evaluation of AI outputs. Results revealed increases in students' self-reported comprehension of AI concepts and their ability to articulate the limitations of fuzzy logic and neural networks in terms of training requirements and data dependency, as well as an increased awareness of ethical implications and potential biases. However, consistent with findings from prior research [1], students' overall motivation to independently seek additional information about AI topics dropped slightly.

The study suggests that embedding AI algorithms within an engineering computational modeling class provides students with a more practical understanding of how machine learning tools operate. By situating AI methods in direct contrast with conventional approaches, students not only gained technical knowledge but also developed an understanding of when such tools should be applied. The paper concludes with a discussion of survey findings, anecdotal student understanding of the algorithms, and implications for expanding AI integration across the engineering curriculum.

Introduction

Artificial intelligence (AI) literacy is becoming more prominent in engineering education. A prior study examined AI literacy in first-year engineering classes [1]. One study examined the use of generative AI in a first-semester engineering project class, and another study investigated the perceived knowledge of AI algorithms in an elective multidisciplinary engineering Grand Challenges course. Unlike prior work that introduced AI conceptually, this study embeds AI algorithms directly alongside classical programming methods within a required second-year computational modeling course, allowing students to compare AI-based and traditional approaches within the same problem context. The course serves as an intermediate step between introductory exposure to AI in freshmen engineering classes and specialization in upper-division classes. Students were introduced to neural networks and fuzzy logic. As the course progressed, they used the tools they learned along with traditional coding techniques to solve the same image recognition problem using different tools. This study explores whether embedding AI alongside classical methods is associated with changes in students' perceived AI literacy, whether an AI learning module enhances awareness of AI limitations, and how student motivation differs between required and elective courses relative to the approach used in [1]. The purpose of this work is to document the instructional design, describe student perceptions, and identify areas for future work. This paper first describes the course and the AI learning module in more detail. Next, the survey instruments and results from the current study are presented. Lastly, a comparison with the previous study is presented, followed by conclusions and future work.

Background

AI is increasingly becoming an important component of undergraduate curriculum, particularly impacting fields such as healthcare, finance, and engineering [2,3]. By including AI instruction, students are better prepared for the job market and future technological innovation. With the inclusion of AI in the core curriculum, students are increasing their AI literacy. AI literacy refers to an understanding of how AI systems function, where they can be applied, and what their limitations are, without requiring deep technical expertise [4]. Developing AI literacy enables students to communicate effectively about AI, recognize opportunities and risks, and apply AI tools to solve problems across a wide range of contexts and systems [5,6].

While the benefits of AI integration in education are well-documented [7, 8], ethical considerations such as bias, fairness, and transparency must also be addressed. Many AI algorithms learn patterns from data, and when training datasets are imbalanced or socially skewed, AI solutions may amplify existing inequalities. Work by Chen et al. and Gichoya et al. highlights that users frequently judge fairness based on perceived system performance rather than an understanding of training data content or validation processes [9,10]. This disconnect underscores the ethical risks associated with using AI systems without sufficient transparency of the development process and reinforces the importance of educating students about how data selection and validation influence outcomes. Further evidence of these concerns is found in reviews of approved AI systems, which reveal that many models are often validated using limited demographic data and a lack of adequate external validation, resulting in biased or unreliable performance across populations [10, 11]. These findings illustrate how technical accuracy metrics can hide inadequate representation in the training data and highlight the need for AI education that explicitly connects system performance with societal impact.

In this study, bias is defined as systemic error or unfair representation arising from training data or model design. By embedding awareness of bias and ethical considerations into AI curricula, academic programs can better prepare students to critically evaluate AI systems. This approach ensures that students develop not only technical awareness but also the ethical reasoning skills necessary to be informed collaborators in shaping equitable AI systems of the future.

Computational Modeling Course

This study was conducted in a Computational Modeling of Engineering Systems class. The course is required in the general engineering degree program at Arizona State University during the students' second year before they choose a concentration in either automotive systems, clean energy systems, electrical systems, mechanical systems, or robotics. The course involved modeling techniques in MATLAB™, Simulink™, and C coding. This study focused on the MATLAB™ portion of the class. Within this portion, students learned matrix algebra, manipulating matrices, flow control and repetition structures, controlled data input/output, user-defined functions, and graphing. Aside from a discussion about generative AI in first-year engineering coursework, the students did not have a formal introduction to AI in their previous classes.

Following the progression of the MATLAB™ portion of the course, the students were presented with one image recognition problem, identifying a red apple, that they solved using various methods. When learning about flow control and repetition structures, students used a FOR loop in several different ways to identify the red apple. They were given a spreadsheet with object identifiers, e.g., size, shape, and color. Based on this information, students used FOR loops to identify the apple in a series of objects such as fruits, balls, frisbees, and a stop sign.

The course then introduced the students to a learning module about AI, computational intelligence (CI), and machine learning. The learning module was similar to the module presented to the Grand Challenges class in the prior work "Incorporating Artificial Intelligence Concepts and Algorithms into Foundational Engineering Courses" [1]. The students learned about feedforward neural networks and the role training data plays in creating an effective solution. The learning module focused on inherent bias in data, the history of training neural networks, and the ethics behind such data. We also discussed how to set up the training data and be accountable for the data and the results. For the neural networks, the students used the same spreadsheet with object identifiers for a red apple for training. The students used the Statistics & Machine Learning toolbox in MATLAB™ and input the spreadsheet values into the classification learner. The students trained 32 different classifiers to recognize a red apple from the input data. They obtained several classifiers with an accuracy of 90% or higher. Next, they used testing data to validate a classifier of their choice. They were able to determine the red apple during this process.

The students were also introduced to fuzzy logic algorithms during the AI learning module, where they used the fuzzy logic designer in MATLAB™. The fuzzy logic module was designed to introduce rule-based reasoning under uncertainty. The module required students to explicitly define membership functions for two input variables (temperature and pulse oximeter values), construct a rule base using if-then inference statements, apply a fuzzy inference mechanism, and implement defuzzification to produce an output classification. Students completed the same healthcare exercise given in [1], where they mapped the input variables to output categories ("healthy", "see a doctor", or "call 911") and observed the resulting decisions.

As one of the last exercises in the MATLAB™ portion of the class, students were then guided through an image processing exercise to determine the red apple. In this exercise, the students uploaded various images, such as a golf ball, a bright red apple, a dark red apple, and a green apple. They determined the RGB components of the images and the percentage of the image that contained red, and used different thresholds to determine if they had an image of a red apple.

Survey Instruments

Students were given a pre-survey before the AI learning module and then a post-survey at the end of the MATLAB™ portion of the class. The pre-survey established baseline levels of comprehension, awareness of limitations, and motivation to learn more about AI, while the post-survey expanded this scope to include measures of awareness of AI limitations, recognition of bias, and critical evaluation of AI outputs. The surveys were created using a 10-point Likert scale that eliminated the neutral response and included ratings from "Strongly Disagree" for 1 to "Strongly Agree" for 10. On the pre-survey, all the questions were closed questions. No open-ended questions or space for comments were included on the pre-survey. The post-survey consisted of closed questions, except for one open-ended question at the end of the survey. For the closed questions, the students were allowed only one answer per question on the numbered scale. The same survey setup with a 10-point Likert scale and closed questions was also used in the previous study [1].

The reliability and consistency of the survey responses were measured using the Cronbach's alpha coefficient value. The Cronbach's alpha coefficient is used as a reliability estimate and is a useful calculation when compared to other reliability estimate algorithms [12]. The Cronbach's alpha score on the pre-survey was 0.70 and 0.88 on the post-survey. These are acceptable values for assessing the internal consistency and reliability of the survey instrument. The two-sided ttest yielded p-values of less than 0.10 on all repeated questions from the pre-survey to the post-survey, suggesting statistically detectable shifts in student self-reported perceptions.

For the pre-survey, 57 students were given the survey, with 47 students completing the survey. The questions from the pre-survey are shown in Figure 1 and are divided by students' perceived comprehension of AI topics, awareness of limitations, and motivation to learn more. The mean student responses are shown in Figure 3 by the question number and highlighted keywords from Figure 1. Figure 3 shows the mean response as the bar, with the first and third quartile responses by the bar lines.

Comprehension

1. **AI Concepts:** I have a good understanding of AI concepts
2. **CI Concepts:** I have a good understanding of CI concepts

Awareness of Limitations

3. **Understand Algorithms:** I have a good understanding of AI algorithms
4. **Understand Limitations:** I understand the limitations of AI

Motivation to Learn more about AI

5. **Interested:** I am very interested in AI tools/products
6. **Learn More:** I want to learn more about AI

Figure 1 Questions divided by focus area on pre-survey.

For the post-survey, 57 students were given the survey, with 42 students completing the survey. The first three questions and the fifth question on the post-survey were the same as on the pre-survey. The questions about AI limitations were expanded in the post-survey. The pre-survey asked about interest in learning more about AI, whereas the post-survey asked about exploring more information about AI algorithms. This variation in learning motivation was mirrored from the previous study [1]. The post-survey did include an open-ended question asking students to identify which approach they preferred for image recognition and to explain the reasoning behind their choice: “Using FOR loops, neural networks, and fuzzy logic, what would you use for an image recognition algorithm and why?”

The question numbers for the post-survey are shown in Figure 2, with the student responses shown in Figure 4, by the following question numbers and highlighted keywords. The student responses for the post-survey are shown in Figure 4, with the mean responses and the first and third quartile indicated.

Comprehension

1. **AI Concepts:** I have a good understanding of AI concepts
2. **CI Concepts:** I have a good understanding of CI concepts

Awareness of Limitations

3. **Understand Algorithms:** I have a good understanding of AI algorithms
4. **Incorrect Predictions:** I recognize the potential consequences of incorrect AI predictions in different contexts (e.g., healthcare, finance, education)
5. **Biases:** I recognize that training datasets may contain inherent biases
6. **Ethical Implications:** I understand the ethical implications of AI making incorrect or biased decisions
7. **Acceptable Errors:** I understand how different applications of AI require different thresholds for acceptable errors (e.g., healthcare)
8. **Critically Evaluate:** I critically evaluate artificial intelligence-generated outputs rather than accepting them at face value

Motivation to Learn more about AI

9. **Interested:** I am very interested in AI tools/products
10. **Explore More:** I intend to explore more information about AI algorithms
11. **Learn Fuzzy Logic:** I enjoyed learning about fuzzy logic
12. **Learn Neural Networks:** I enjoyed learning about neural networks

Figure 2 Questions divided by focus area on post-survey.

Results

In the pre-survey results, the students had a mean result of 5.60 for a good understanding of AI concepts and a mean result of 4.96 for a good understanding of CI concepts. The mean result fell to 4.04 for understanding AI algorithms, with the first quartile of data at a low value of two. The mean result increased to 5.57 for understanding the limitations of AI. The mean results for being interested in AI tools and wanting to learn more about AI were high at 7.17 and 7.74, respectively, as shown in Figure 3.

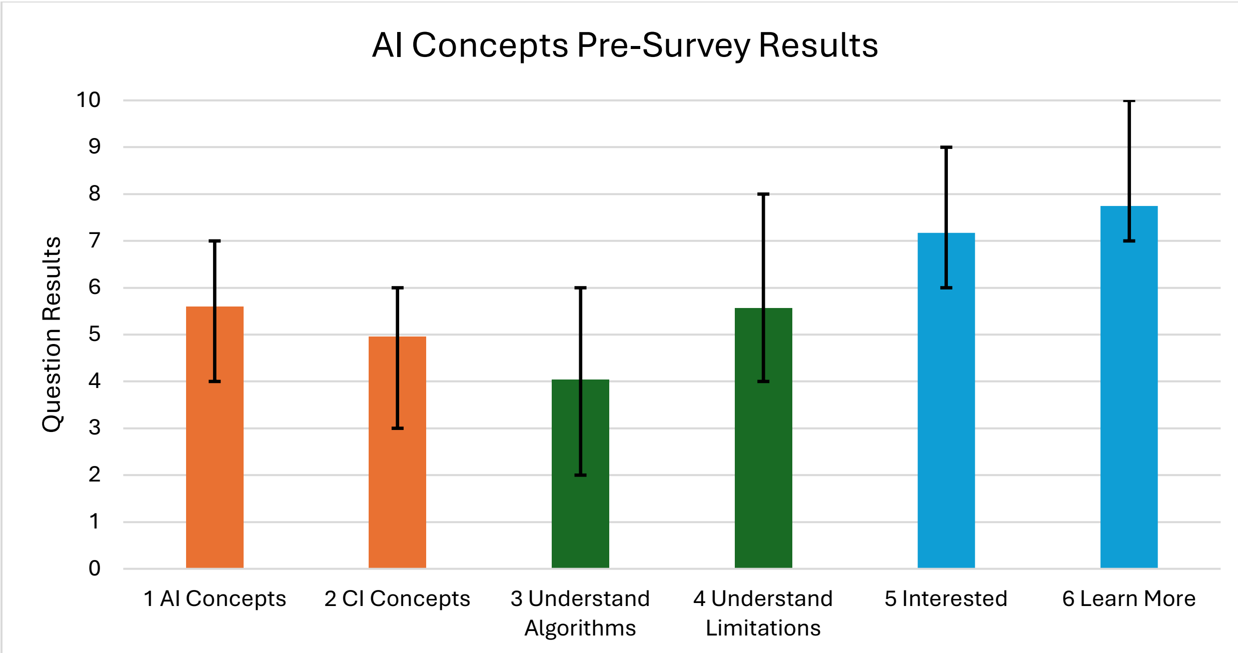

Figure 3 Student responses to pre-survey with bars indicating mean responses and bar lines indicating the first and third quartiles of the responses.

The first three questions in the post-survey were repeated from the pre-survey, and there was significant growth. The post-survey had a mean result of 6.86 (+1.26) for a good understanding of AI concepts and a mean result of 6.79 (+1.83) for a good understanding of CI concepts, more than a point increase for both, and an increase in first quartile data from four and three up to six for both questions. The mean for a good understanding of AI algorithms rose to 6.43 (+2.39) on the post-survey, a more than two-point increase, with the first quartile increasing three points. The next five questions about the limitations all had mean results above eight, as shown below.

- I recognize the potential consequences of incorrect AI predictions in different contexts (e.g., healthcare, finance, education): 8.64
- I recognize that training datasets may contain inherent biases: 8.21
- I understand the ethical implications of AI making incorrect or biased decisions: 8.67

- I understand how different applications of AI require different thresholds for acceptable errors (e.g., healthcare): 8.45
- I critically evaluate artificial intelligence-generated outputs rather than accepting them at face value: 8.22

The next question, repeated from the pre-survey of being interested in AI tools, went up slightly (+0.62) with a mean response of 7.79. The mean response for seeking out more information about AI algorithms was 7.49, which was slightly lower (-0.25) than wanting to learn more about AI on the pre-survey. The last two questions asked about the enjoyment of learning about fuzzy logic and neural networks, and scored mean responses of 7.62 and 7.64, respectively.

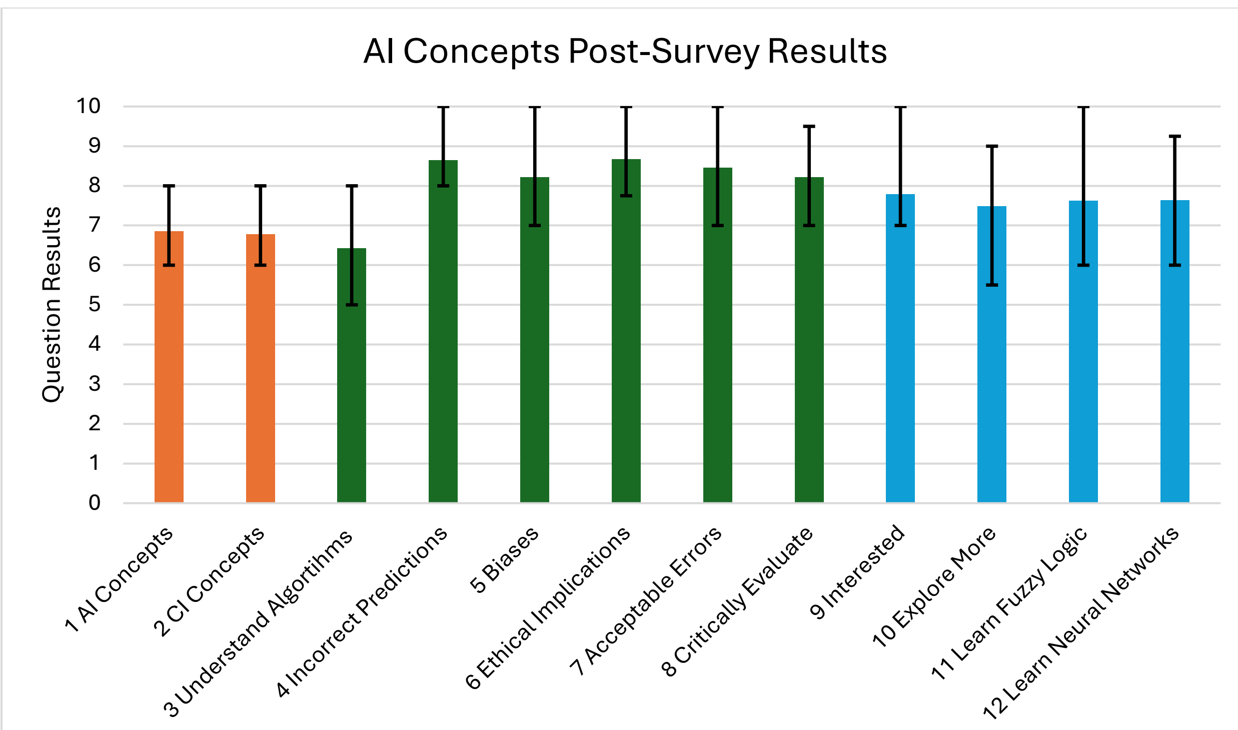

Figure 4 Student responses to post-survey with bars indicating mean responses and bar lines indicating the first and third quartiles of the responses.

On the open-ended question, the students overwhelmingly chose neural networks for the answer to “Using FOR loops, neural networks, and fuzzy logic, what would you use for an image recognition algorithm and why?” A few written examples from the surveys are shown below:

- **“** I would choose to use a neural network for image recognition, because it would be easy for a beginning coder to use, such as myself. It also allows me to use large amounts of noisy data.“
- **“**I would say a neural network is a good in between of both worlds for image recognition due to the complexity of teaching a code to recognize different objects requires a lot of data and training. They also have the ability to recognize an object even if it hasn't looked at it at that exact angle. That's why a neural network would be the top pick for this application.”
- “The neural network can adapt and would require some training but that would also allow it to process the datasets. Allowing it to compare something in the image to other similar known images to find the object.”
- “What I would pick for image recognition is neural networks. Much like the apple example we used, it may be difficult at first to nail down what you want the neural network to do, but once you get it set up, it is just fine tuning and testing. One could simply add more checks to increase the accuracy as well.”
- “I would use neural networks for image recognition because it is built to find patterns and similarities based on the large sums of data it has access to. The more data it is able to use the accurate the output the neural network will give.”

- “Allowing the neural network to deal with the nuances makes the most sense. The user would simply have to tweak the weighting and dataset as testing progresses.”

Overall, the results indicated increases in students’ self-reported AI comprehension and awareness of AI limitations and risks. The results also showed a decline in students’ motivation to seek out more information about AI algorithms. Anecdotally, responses to the open-ended question suggested that students gained familiarity with the AI approaches presented and were able to describe how they might be applied in a specific context.

Comparison of the Scaffolded Studies

The pre-survey mean results for comprehension and awareness of limitations were lower in this current study than in the previous study [1]. The prior study had a smaller sample size of eighteen students and was based on students in the Grand Challenges Scholar Program. The current study was conducted in a required course with a larger sample size. The pre- and post-surveys in the previous work also asked about wanting to learn more about AI and seeking out more information. Similar to this study, there was a slight drop in interest. A comparison of the pre-survey results for both studies is shown in Figure 5, and a comparison of the post-survey results is shown in Figure 6.

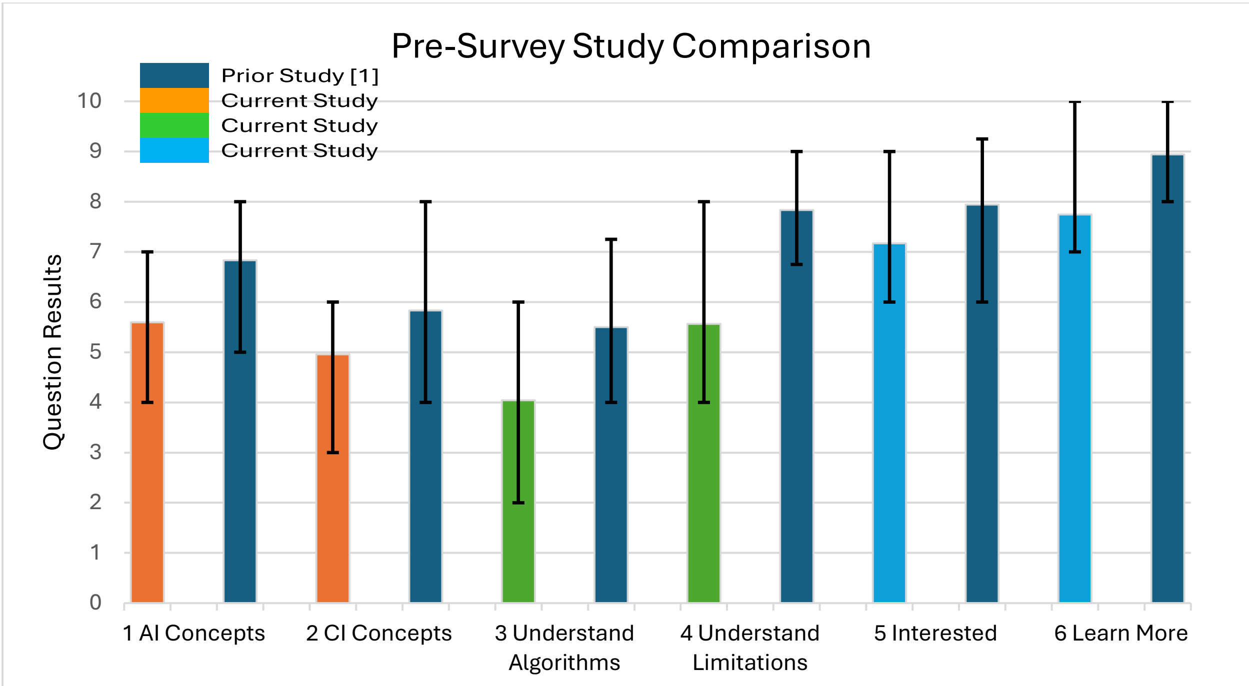

Figure 5 Comparison of the current study and prior study [1] pre-survey results, with bars indicating mean responses and bar lines indicating the first and third quartiles of the responses.

All the mean responses from the current study were lower than those from the prior study. Both studies had a marked increase in the understanding of AI and CI concepts and algorithms. Both studies had the same trend with the last question, the desire to seek more information about AI algorithms dropped in both studies. This trend was initially considered an anomaly due to the small sample size and possibly increased confidence in what the students had learned. However, its recurrence in the current study using a larger sample size and a required course, as opposed to an elective course, suggests a consistent pattern. The key points from both studies are that AI literacy improved for both classes, while the interest in future investigation of the topic fell slightly.

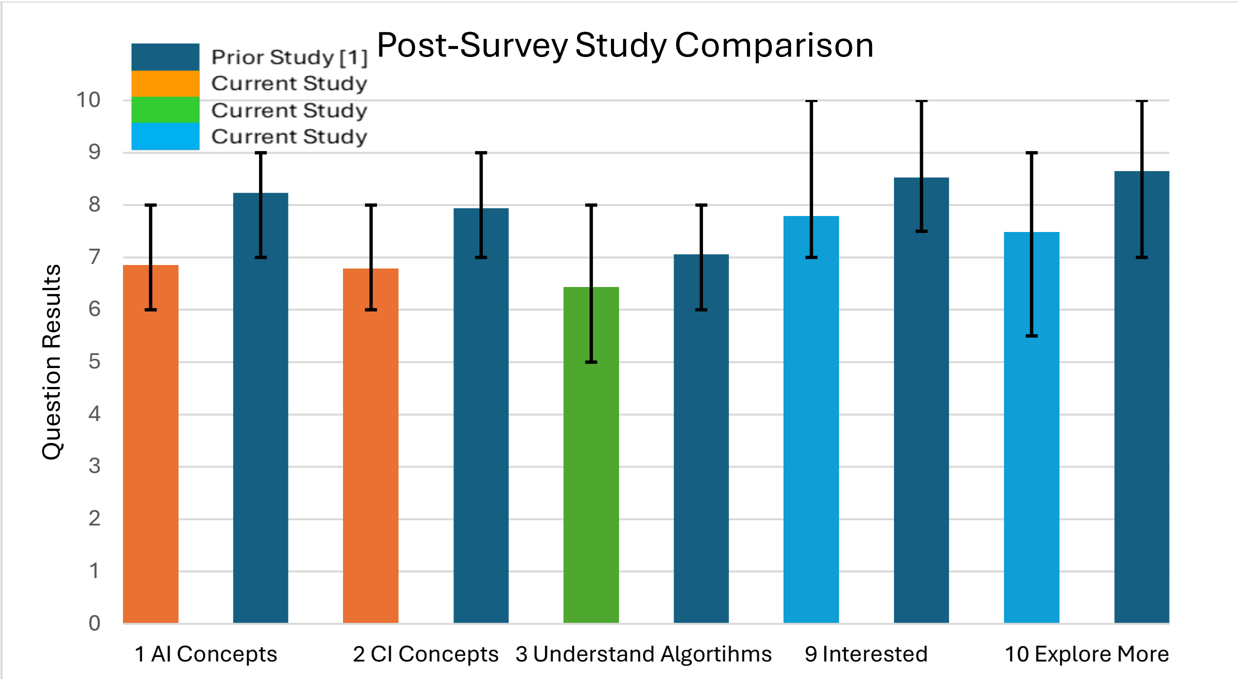

Figure 6 Comparison of the current study and prior study [1] post-survey results, with bars indicating mean responses and bar lines indicating the first and third quartiles of the responses.

Limitations

This study has several limitations. Data for each iteration were collected from a single course offering with a limited sample size in both instances. The survey instrument relied on self-reported student perceptions of understanding rather than performance-based measures. The perception data did provide insight into student confidence and engagement. The AI modules were implemented within the constraints of an existing course structure, limiting the depth of technical knowledge within the allotted instructional time. There was conceptual exposure to increase AI literacy rather than comprehensive technical mastery. This work represents an early-state curriculum innovation, where future iterations will incorporate refined survey instruments and multi-course implementation.

Conclusion and Future Work

This study suggests that embedding an AI learning module in a second-year engineering computational modeling course can enhance the students' AI literacy in terms of conceptual understanding and limitations. By integrating neural networks and fuzzy logic alongside traditional programming approaches in MATLAB™, students were able to use AI algorithms as a practical engineering tool. The repeated application of multiple solution strategies for a single image recognition problem enabled a direct comparison between classical coding methods and AI-based techniques.

Survey results indicated increases in students' perceived understanding of AI concepts and algorithms. The post-survey responses revealed strong awareness of AI limitations, including the role of training data, the presence of bias, and the ethical consequences of incorrect predictions. Mean responses exceeding eight on all ethics and limitation-related questions suggest that students engaged with considerations of bias, data transparency, and risk.

Students primarily identified neural networks as the preferred approach for image recognition tasks. Student explanations reflected an understanding of tradeoffs, including the need for sufficient training data and iterative tuning. This suggests that students were not simply favoring AI tools due to the newness in class, but they were developing informed judgment about when and why such methods were appropriate. As observed both in this study and in previous research, increases in AI literacy did not translate into a corresponding increase in students' motivation to seek out additional AI-related information. This may reflect increased confidence or perceived sufficiency of current knowledge rather than disinterest. The recurrence of this trend across different courses and student populations suggests that motivation merits further investigation.

Future work will focus on further scaffolding AI literacy topics across additional courses and monitoring the students' perceived knowledge and motivation as they progress through their academic path. This will be achieved by expanding the sample across multiple course sections and incorporating performance-based assessments to evaluate learning outcomes. Overall, the findings suggest that embedding AI algorithms within foundational engineering courses may be a promising approach for supporting the development of AI literacy. This approach allows students to develop practical skills, awareness of AI limitations, and critical judgment early in their academic careers, preparing them for success in the workforce.

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