2026 ASEE ANNUAL CONFERENCE June 21–24, 2026 | Charlotte Convention Center, NC
Host Sponsor UNC Charlotte
Paper ID #53021

# Impact of AI-assisted Computer-Aided Manufacturing Interfaces on Engineering Students' CNC Programming Skills and Strategic Thinking

**David Lesser, University of California, San Diego**
**Dr. Maziar Ghazinejad, University of California, San Diego**

Maziar Ghazinejad is an Associate teaching professor in Mechanical and Aerospace Engineering Department at UC San Diego. He received his Ph.D. in mechanical engineering from UC Riverside in 2012 and holds M.S. degrees in mechanical and electrical engineer

# Impact of AI-assisted Computer-Aided Manufacturing Interfaces on Engineering Students' CNC Programming Skills and Strategic Thinking


## 1. Abstract

Artificial intelligence interfaces are set to transform computer-aided design and manufacturing, and more broadly, engineering pedagogy. An example of this trending development in CAM is AI-assisted toolpath planning, which facilitates the configuration of tooling and toolpaths. Engineering students, from various majors, are often tasked with developing CNC toolpaths to fabricate parts. Configuring these codes usually involves algorithmic thinking that integrates spatial visualization, knowledge of industry protocols, and toolpathing. This work-in-progress aims to examine the impact of AI tools on short and long-term goals among engineering students. The main research questions are (1) Does AI assistance improve the speed and accuracy of completing CNC projects? (2) Will relying on AI tools come at the expense of students' higher-order thinking skills? Participants are split into two groups, AI-assisted and non-AI-assisted. Students manufacture a series of parts of increasing difficulty and decreasing tutorial support with their assigned workflow, setting up the CNC toolpaths and running the machine. The manufactured parts will undergo a structured acceptance test to assess the quality of students' toolpath planning and machining proficiency across both student groups (AI-assisted and non-AI-assisted). Finally, students are tested for a deeper understanding of CAM by being tasked with evaluating a variety of existing machining setups for errors and inefficiencies. All assessment instruments, including the pre- and post-training CAM knowledge test, the students' manufactured parts acceptance test results, and the instructors' structured observations, will serve as data sources for addressing the study's two research questions.


## 2. Introduction, problem statement, and research questions

As visions of the Fourth Industrial Revolution gain momentum across today's technological landscape, the role of modern manufacturing is becoming increasingly critical. Contemporary manufacturing practices are shaped by advances in robotics, digital manufacturing, artificial intelligence, and additive manufacturing [1-8]. The inevitable integration of these innovations is significantly reshaping the manufacturing industry and manufacturing education [9-11].

Among these technological drivers, artificial intelligence has taken center stage and drawn the attention of manufacturing experts, practitioners, and students alike [6, 11]. This is partly due to fast (though not necessarily optimal) results and the ease of use of AI-enhanced interfaces. Computer-aided manufacturing (CAM) is a prime example of this trend, with new CAM software including AI -generated toolpaths [3,4,6, and 12]. The intended outcome of these tools is to facilitate the manufacturing process and increase users' productivity. While these AI innovations are poised to profoundly enhance manufacturing practice, these advanced methodologies are not included in standard engineering programs and pedagogy. This is despite the widespread availability of AI-enhanced tools, which have given today's STEM students unprecedented access to generative models that they now use regularly, whether or not they are formally part of the academic program [13-15].

Given the rapidly evolving landscapes of technology and education, it is crucial and timely to adopt an evidence-based strategy to investigate the measurable impacts of integrating modern data science tools into manufacturing engineering education and other STEM areas [15-20]. In this work-in-progress report, we describe our study, which uses a well-defined CAM training short course to investigate how AI interfaces influence engineering students' field-specific competencies and higher-order thinking skills. Our working hypothesis is that while AI tools will likely help with the short-term goals of CAM assignments, unsupervised reliance on them, particularly in the early stages of learning for STEM students, will lead to a shallower understanding of core manufacturing concepts and tools. The project will address two essential research questions to examine the hypothesis outlined. Does AI assistance improve the speed and accuracy of completing CNC projects? And will frequent reliance on AI tools come at the expense of students' higher-order thinking skills?

**3. Curriculum and experiment procedure**

A pool of students is recruited with modest prior experience with CNC programming, having taken the mechanical engineering department's machining course, a one-credit hands-on training in manual and CNC machining. The participants are paired up and split into two groups, AI-assisted and non-AI-assisted (traditional). Each group receives a short training session on their assigned workflow and participates in shared practical workshops on machining and metrology. Students in the non-AI-assisted group will use Fusion360's 'Manufacturing' workflow to create the toolpaths manually, relying heavily on tutorial videos and ancillary material from the TITANS of CNC Academy units on making the parts (along with additional support from the teaching staff) [21]. Students in the AI-assisted group use the CAM Assist tool from CloudNC [22], which automatically generates toolpaths within Fusion 360's Manufacturing workflow. These students will follow an internally developed tutorial.

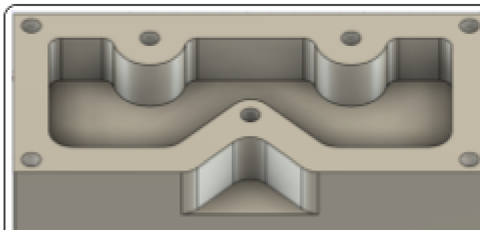

Figure 1: The first part students manufacture in the course: a realistic, beginner-friendly part designed by *TITANS of CNC* for part one of their CNC Academy. This part is intended to be relatively simple, with only flat, '2.5D' features that can be produced with relatively few, simpler toolpaths.

The main workshop is presented across three weekly group meetings, with individual work in between. In the first week, the curriculum is presented, the first assignment part is described, and students are instructed to follow the relevant tutorial guide for their assigned workflow (traditional or AI-assisted). Physical setup and running of the milling machine is also presented. The first part is relatively simple, with basic 2D features requiring only a few simple tool paths

(Figure 1). Over the next week, students are expected to complete the toolpath scripting for their part, meet with a makerspace staff member to have the part checked for safety, and (if approved) manufacture it on the Tormach 1100MX CNC mill. The total time commitment for these tasks is estimated to be 2-3 hours. Table 1 shows the Inspection Report for Part One’s CNC Workshop.

Table 1. Inspection Report form Part One’s CNC Workshop

| **Test** | **Requirement** | **Measured** | **Pass?** |
|---|---|---|---|
| Thread Fit | 10-32 screw fits in all holes, .375” minimum | | |
| Wall thickness (each segment) | .300” +/- .005 | | |
| Part envelope | Width: < 4.005”<br>Height < .755”<br>Depth < 2.005” | | |
| Pocket | Depth .500” +/- .005”<br>Width 3.400” +/-.002”<br>1.300” +/- .005” | | |
| Burrs | All edges broken | | |

At the following meeting, a discussion of acceptance testing/judging criteria is presented: real-world use cases, such as bearing fits, or precision alignment requirements, are presented as foundational justification for calling out specific dimensional tolerances. Once the critical tolerances of the first part are (retroactively) stated, two practical hands-on lectures ensue. The first introduces the notion of different similar processes and the tradeoff of precision for cost and complexity (e.g., drilling vs. reaming vs. boring). The last topic covers empirical methods for testing the acceptability of fabricated parts, using simple, standard processes like go/no-go gauges and measuring tools like calipers. Finally, a second part is presented, with more complex 3d geometries. Unlike the first part, the second part is also presented alongside a brief discussion of the critical functional

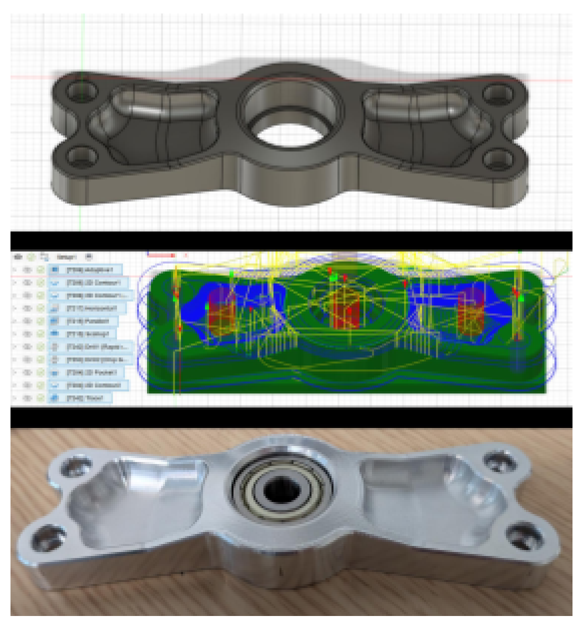

Figure 2: The second part used in workshop (also designed by *TITANS of CNC*) where more complex 3D geometries are introduced. At top is the starting 3d model; in the middle are several machining operations to cut the piece from stock; and finally the finished part (bottom), with pressed bearing.

requirements, so students can factor them in as they set up the toolpaths and machining. As before, students are expected to complete the toolpath setup and manufacture the part as homework before the final week of training.

At the final meeting, the second part is discussed and subjected to acceptance testing. Beyond the traditional metrology tools presented in the prior class, more advanced CMM tools are introduced, enabling faster, more complex geometric tolerancing by digitizing the physical part and comparing it against the target 3D model. A third part is introduced, now without an accompanying step-by-step tutorial. Lastly, a short written test is given, asking students to assess example toolpaths and identify errors and omissions.

## 4. Evaluation Process, Results, and Discussion (work in progress)

A four-point-based grading scale, consistent with the ABET standard [23, 24] is used to assess the student learning outcome in toolpath planning and execution and machining proficiency, as well as the geometric accuracy of each of the three completed parts. Additionally, each student participates in a written assessment.

Vis-à-vis toolpath planning and execution, students are assessed, essentially, on their ability to complete the assignment efficiently and self-sufficiently through structured observation by the instruction team. To what extent do students seek tutoring from staff or other outside resources? Even more critically, are students' proposed toolpaths judged to be safe to run, or are they sent back for correction? When run, do they execute efficiently and as planned, or do they need to be stopped and modified? Do parts need any rework? Is it necessary to scrap the part and start over? While the degree to which students struggle with the task is a key marker of subject-matter mastery, care is taken to avoid influencing student behavior, such as discouraging students from seeking help because they worry it might affect their grade.

Figure 3: Physical acceptance testing methods. Above, checking bores with gauge pins. Center, measuring surface height using a surface plate and height gauge. Below, practical tests such as a bearing press fit.

Additionally, each part includes an itemized checklist for judging, with specific, real-world requirements and resulting dimensional constraints. Students' work is graded on the parts ability to pass a series of go/no-go metrology tests and real-world criteria (e.g., press-fitting a bearing into a bore). Moreover, to quantitatively evaluate students' manufactured parts during training, we use the PC-DMIS program in conjunction with a Hexagon Absolute arm equipped with an integral laser scanner. This enables creating a 3D scan of manufactured parts and directly comparing with their original CAD to quantify (i) surface finish and (ii) accuracy of 3D surfaces.

Lastly, students are evaluated by asking them to judge a variety of existing machining setups for errors and inefficiencies: some good, some bad; some with obvious mistakes, others more subtle. A short survey also asks students to self-assess their confidence in the topic of machining and how much it has improved over the course of the workshop. With our six practical grades and the assessments, a trend over the course of the project can then be determined for each group, and from there, the relative degree of improvement between the two cohorts can be compared. Table 2 outlines the assessment details and rubric used for each performance category.

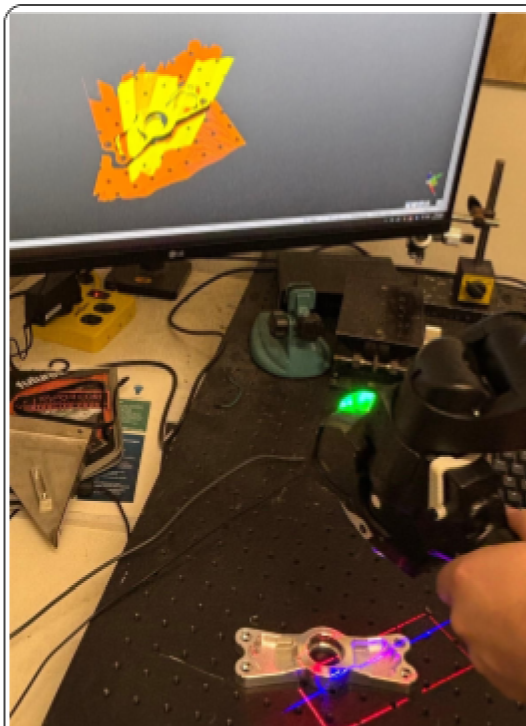

Figure 4: Using the Hexagon Absolute Arm and laser scanner to digitize a part.

For the first and second parts, students were broadly successful in efficiently completing the parts, overwhelmingly earning scores of 4 out of 4 on their proficiency. While many did not achieve complete success at meeting the exact criteria specified, the nature of the activity was such that the exact judging criteria were not shared until the part was completed, without real opportunity for the students to rework or remake the parts to meet criteria, as one would in a professional setting. As students had prior CNC experience and were given clear directions, it is not surprising that they generally did well completing parts one and two.

For the practical test, the students were given two Fusion360 files containing toolpaths prepared with a multitude of errors, omissions, and inefficiencies, approximately 26 in total. A wide gamut of issues were included: incorrect speeds and feeds for the tool selected; tool holder collision with the part; rough machining a feature oversized without subsequent finishing; both gratuitously aggressive and conservative cuts (either breaking tools or wasting lots of time, respectively); and incorrect part fiducial choice. Here we see the most statistically significant differentiator between groups. While no student came close to catching all the errors (the best caught only half), the AI-assisted group caught significantly more errors, with a mean of 7 per student, compared with the traditional students, who averaged only 4.5 per student.

Table 2. The standard rubric is used to assess students' learning outcomes during the training

| Performance Indicator | 1- Not acceptable | 2. Below Expectations | 3. Meets expectations | 4- Exceeds Expectations |
|---|---|---|---|---|
| Toolpath planning | Toolpaths are not complete | Toolpaths are completed, but contain significant errors (likely requiring intervention from instructors to avoid dangerous scenarios) | Students produce largely acceptable, albeit unoptimized, toolpaths | Students display mastery of optimizing toolpaths to maximize dimensional accuracy, tool life, and cycle time |
| Execution and machining proficiency | Machining is incomplete, with extensive setup and execution errors | Machining is complete, but students need extensive support; parts may need rework or repair | Students are relatively self-sufficient. Errors may occur, but students recognize issues as they occur and adapt. | Job is set up and run efficiently and without error. |
| Geometrical Accuracy | Machining steps are not all completed, or part is grossly out of spec. | Students parts are completed, but fail some tests | Student parts are (largely) acceptable, perhaps after remaking or reworking the part. | Student parts meet all requirements with no corrections necessary |
| Written Assessment | Students largely fail to recognize important errors, and introduce new issues | Students improve toolpath quality, but significant issues remain | Students’ corrections are largely adequate to produce a good part, but not optimal | Students corrections are optimal |

This outcome is perhaps explainable given the degree to which the AI-assisted group training included a significant component of correcting issues generated by the AI, a topic the other group (following instructions from a CNC expert) did not need to cover. Interestingly, while the AI group averaged better, they had significantly greater scatter (standard deviation of 4.2 vs 1.4) and a significantly higher rate of suggesting changes that were judged as harmful rather than helpful to the outcome (6 in total versus 1 for the AI and non-AI groups). The most common errors correctly identified are the ones that the toolpath simulation automatically calls out, namely the toolholder collisions.  The least common errors detected were wholesale omissions; few students noticed features that were not machined, even when relatively obvious (e.g. through bore not machined all the way through).

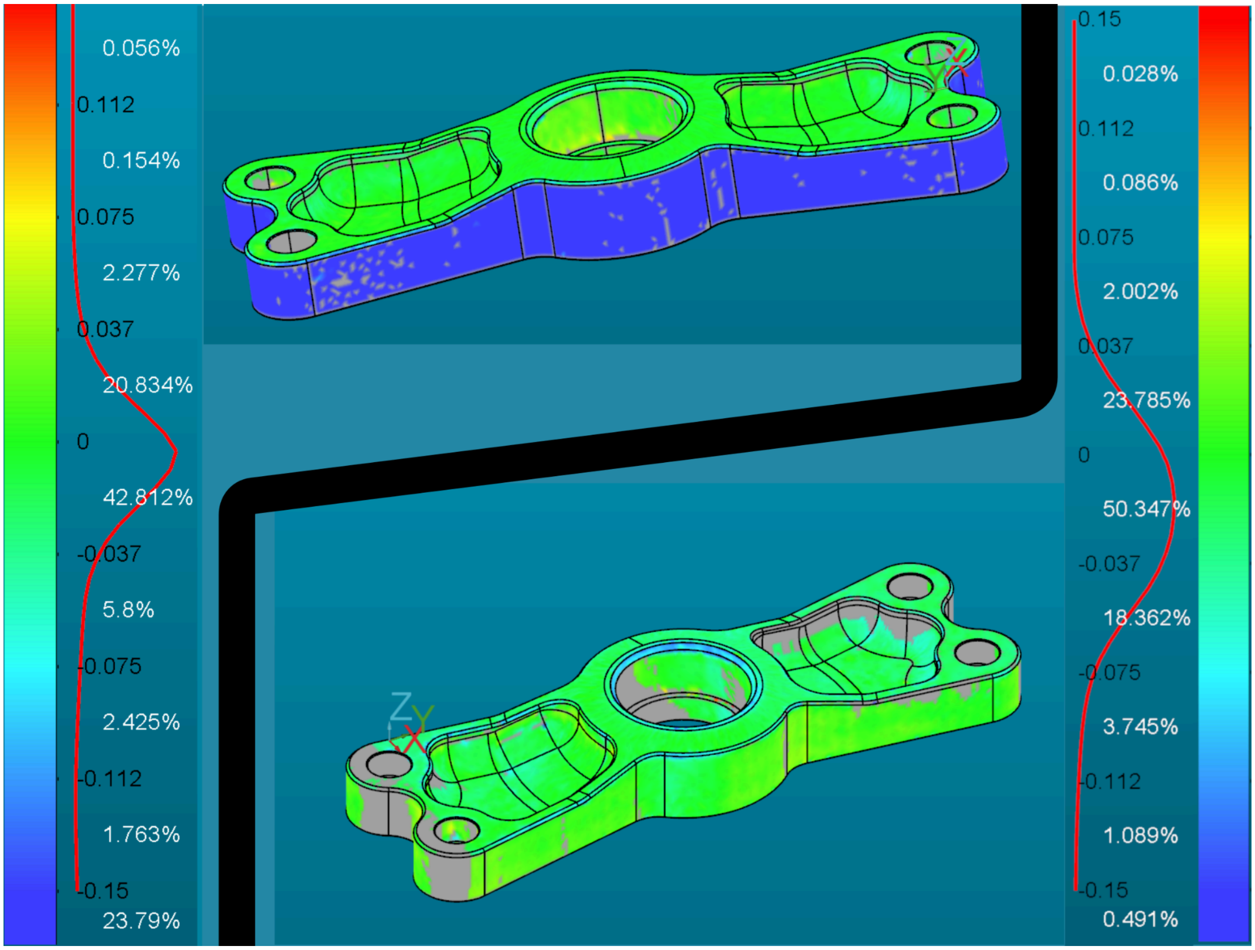


Figure 5: Below and at right, a PC-DMIS analysis of a 4 out of 4 student submission for the 2nd practical assignment.  A significant majority of the part, ~75% is within the smallest error deviation of +/- ≤ 37 um, and only around 0.5% exceeds 150um error from nominal.  Left and above, a submission graded 2. Most of the part is within tolerance, but the outside of the part was machined improperly, resulting in a significant error.

In the next section of this work-in-progress study, we will analyze students' CNC programming skills through an open-ended project. Unlike the previous parts, this final assignment will not include a step-by-step tutorial, to duplocate real-worls scenario. It will emphasize more complex, and consequential manufacturing skills related to tooling. Specifically, students will focus on machining injection molds, which will be used for molding parts. This culminating experience will enable both students and instructors to observe the impacts of CNC skills and strategic thinking in the context of mass-manufactured parts. We will discuss this analysis in detail in our upcoming report.

## 5. Conclusion and future work

Comparing the results of each group's work (AI-assisted versus human-driven CAM job sequences) provides valuable insights into the impact of AI-assisted CAM Interfaces on engineering students' learning of CNC Programming Skills. Although we are still in the early stages of this study, one key insight that has emerged is that AI-assisted interfaces will require the development of new learning and teaching methods. These methods should integrate AI tools into engineering curricula while also enhancing students' critical thinking and deep understanding of STEM subjects. Early outcomes of the study suggest that higher-order thinking skills are essential for effectively utilizing AI solutions in manufacturing engineering. These insights should inform efficient and future-proof pedagogical techniques for training students interested in machining. This includes not only those pursuing a career as machinists but also mechanical, manufacturing, and aerospace engineering students who can significantly improve their understanding of design for manufacturing through practical experience. Additionally, R&D engineers, prototypers, entrepreneurs, and a wide array of makers would benefit from acquiring these additional skills.

In the future, we plan to expand and repeat the training sessions with additional groups of students, increasing the diversity of participants' prior experience, ranging from less to more experienced individuals. Additionally, we aim to track students' usage of the machine shop to evaluate longer-term impacts and address the following questions: (a) do students tend to stick with their randomly assigned workflows, or do they switch? (b) Is there a correlation between a specific workflow and the likelihood that students will independently pursue machining projects and successfully complete them?

## References

1. Khang, Alex, et al. "Enabling the future of manufacturing: integration of robotics and IoT to smart factory infrastructure in industry 4.0." Handbook of Research on AI-Based Technologies and Applications in the Era of the Metaverse. IGI Global, 2023. 25-50.

2. Parmar, Hetal, et al. "Advanced robotics and additive manufacturing of composites: towards a new era in Industry 4.0." Materials and manufacturing processes 37.5 (2022): 483-517.

3. Mathew, Dennise, N. C. Brintha, and JT Winowlin Jappes. "Artificial intelligence powered automation for industry 4.0." New horizons for Industry 4.0 in modern business. Cham: Springer International Publishing, 2023. 1-28.

4. Prashar, Gaurav, Hitesh Vasudev, and Dharam Bhuddhi. "Additive manufacturing: expanding 3D printing horizon in industry 4.0." International Journal on Interactive Design and Manufacturing (IJIDeM) 17.5 (2023): 2221-2235.

5. Javaid, Mohd, et al. "Enabling flexible manufacturing system (FMS) through the applications of industry 4.0 technologies." Internet of Things and Cyber-Physical Systems 2 (2022): 49-62.

6. Soori, Mohsen, Behrooz Arezoo, and Roza Dastres. "Machine learning and artificial intelligence in CNC machine tools, a review." Sustainable Manufacturing and Service Economics 2 (2023): 100009.

7. Uysalel, Can, Jackelin Cotrina, and Maziar Ghazinejad. "Automated defect characterization and physics-based performance modeling of additively manufactured metals with vision transformers." MRS Advances 10.20 (2025): 2337-2343.

8. Kumar, Anil, et al. "A framework for assessing social acceptability of industry 4.0 technologies for the development of digital manufacturing." Technological Forecasting and Social Change 174 (2022): 121217.

9. Broo, Didem Gürdür, Okyay Kaynak, and Sadiq M. Sait. "Rethinking engineering education at the age of industry 5.0." Journal of Industrial Information Integration 25 (2022): 100311.

10. Moraes, Eduardo Baldo, et al. "Integration of Industry 4.0 technologies with Education 4.0: advantages for improvements in learning." Interactive Technology and Smart Education 20.2 (2023): 271-287.

11. Haderer, Bernhard, and Monica Ciolacu. "Education 4.0: artificial intelligence assisted task-and time planning system." Procedia computer science 200 (2022): 1328-1337.

12. Cam Assist/CloudNC : https://www.cloudnc.com/ [Accessed January 2026]

13. Johri, Aditya, et al. "Generative artificial intelligence and engineering education." Journal of Engineering Education 112.3 (2023).

14. Qadir, Junaid. "Engineering education in the era of ChatGPT: Promise and pitfalls of generative AI for education." 2023 IEEE global engineering education conference (EDUCON). IEEE, 2023.

15. Walter, Yoshija. "Embracing the future of Artificial Intelligence in the classroom: the relevance of AI literacy, prompt engineering, and critical thinking in modern education." International Journal of Educational Technology in Higher Education 21.1 (2024): 15.

16. Ghazinejad, Maziar, Farbod Khoshnoud, and Stephen Porter. "Enhancing interactive learning in engineering classes by implementing virtual laboratories." 2021 IEEE Frontiers in Education Conference (FIE). IEEE, 2021.

17. Delson, Nathan, et al. "Can oral exams increase student performance and motivation?." 2022 ASEE Annual Conference & Exposition. 2022.

18. Lamata, Lucas, et al. "Quantum mechatronics." Electronics 10.20 (2021): 2483.

19. Uysalel, Can, Zachary Fox, and Maziar Ghazinejad. "Using AI Interactive Interfaces in Design of Machine Elements Education." 2024 ASEE Annual Conference & Exposition. 2024.

20. Hernandez-de-Menendez, Marcela, Carlos A. Escobar Díaz, and Ruben Morales-Menendez. "Engineering education for smart 4.0 technology: a review." International Journal on Interactive Design and Manufacturing (IJIDeM) 14.3 (2020): 789-803.

21. TITANS of CNC Academy. [https://academy.titansofcnc.com/category/mill-building-blocks] [Accessed Dec 22, 2025].

22. CloudNC. [https://www.cloudnc.com/] [Accessed Dec 22, 2025]

23. Accreditation Board for Engineering and Technology [https://assessment.abet.org/]

24. Garry, Byron. "Examples of rubrics used to assess ABET student outcomes in a capstone course." 2011 North Midwest Section. 2021.