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Auto-graded CAD Assignments for Mastery-Based Learning

Dr. Kellie M Halloran, University of Illinois at Urbana - Champaign

Kellie Halloran is a Teaching Assistant Professor in Mechanical Science and Engineering at the University of Illinois Urbana-Champaign. She holds a BS, MS, and PhD in Mechanical Engineering from the University of Illinois and is currently investigating ways to engage undergraduate students and encourage curiosity and creativity in larger engineering classes.

Dr. Kevin Wandke, University of Illinois at Urbana - Champaign

Kevin Wandke is an Assistant Teaching Professor in the department of Mechanical Science and Engineering at the University of Illinois Urbana-Champaign where he focuses on soft robotics, AI and pedagogy. Kevin received his B.S in Mechanical Engineering from the University of Illinois Urbana-Champaign in 2019, and his PhD in Electrical Engineering from the University of Illinois Urbana-Champaign in 2024.

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Abstract

This complete evidence-based practice paper describes the development of an auto-grading system that allows for mastery-based learning in a large first-year engineering design course. An early skill first-year engineering students develop is the ability to design and model parts using Computer-Aided Design (CAD) software. CAD proficiency is foundational to a host of engineering disciplines as it enables engineers to design, fabricate and analyze parts and assemblies. To develop CAD proficiency, many introductory courses require students to practice creating parts that meet certain specifications. As students practice these tasks they learn typical CAD functions such as extrudes, fillets, lofts, holes, and assembling and dimensioning parts. These lessons build off one another: sketches are extruded into bodies, which have features added to them, and parts and drawings are created and assembled together. The sequential nature of CAD therefore means that before moving on to more complex CAD tasks, it is critical that students develop a robust understanding of the fundamental tasks.

Given this sequential and skill-dependent nature of CAD, teaching methods that emphasize mastery and iterative learning can be particularly effective. Mastery-based learning has emerged as an effective method for students to develop skills that build off of one another. In mastery-based learning, students are allowed to correct and resubmit work many times until it is correct. The idea behind this approach is that students must demonstrate mastery over a course topic before they are able to move on to subsequent topics.

Despite clear advantages, mastery learning is usually not utilized in large CAD courses. This is in large part due to logistical and resource constraints that make it difficult to quickly provide detailed feedback on student work. Instead, students often wait weeks to discover that they made an error. As a result, students may fail to fully develop their CAD skills, which will detract from their ability to be an effective engineer in the future.

After identifying these deficiencies in the current state of CAD education and grading, we developed a method to provide students with instantaneous feedback on the quality of the CAD models they have created via automatically graded CAD assignments. To achieve this goal, we developed a software solution that leverages Autodesk Fusion's Application Programming Interface (API) to provide immediate feedback to students about their CAD models. The software collects data on part geometry, sketching constraints, and other parameters that an instructor can choose to have graded. This program then parses this data to provides immediate feedback on students' designs and enables students to engage in mastery-based learning as they are allowed multiple submissions with immediate feedback after each attempt. In addition to the API program, we also utilize PrairieLearn, an open-source mastery-based learning platform, to provide feedback and track student submissions.

This approach has been used successfully at a large Midwest University and student feedback has been positive. Overall, the auto-grader program improves the types and frequency of feedback available to students. The program also significantly reduces the time that the course staff allocates for grading, and creates more time to develop course materials and provide additional support for

students. Current plans include expansion to more assignments with various submission requirements and formats, and mapping use of the API program to learning outcomes.

Introduction

One of the most critical skills for many young engineers to develop is the ability to design and model physical objects using Computer-Aided Design (CAD) software. When learning how to use a CAD system, students usually learn how to interact with the software in a regimented step-by-step manner where each new skill builds directly off of several previous ones. This method of education is well-suited for mastery-based learning. One of the core ideas of mastery-based learning is that education is not a one-size-fits-all endeavor, and that it is important to connect instruction with the unique needs of students [1]. In practice this usually looks like giving students multiple attempts to show mastery on a topic, or utilizing frequent formative assessments. In recent years, it has been shown that mastery-based learning can result in a significant increase in student grades [2]. Furthermore, mastery-based learning can encourage students to focus more on learning and skill development, as opposed to their grades [3]. Despite these clear advantages, mastery-based grading is not widely adopted, as it poses significant challenges such as creating additional grading and complicating course logistics [4, 5].

There are several barriers to implementing mastery-based learning in CAD courses. While it is widely accepted that mastery-based learning in CAD will require some sort of automatic grader, the exact mechanism by which an automatic CAD grading system would function is still an open question. One of the most significant questions is determining what type of data should be collected for grading. A simple approach is to use overall geometric information such as the center of mass and volume, but this approach can vary depending on modeling technique and cause errors [6]. Other approaches make use of the model history to examine how a part was made, in addition to geometry. However, these approaches only work for highly constrained modeling tasks [6].

Neither of these grading approaches is perfect, but it is important to note that human graders make errors when grading CAD models as well [7]. Comparisons between human graders and automated grading systems often show discrepancies, and data indicates that these errors are usually the result of human mistakes [8].

There are a few existing CAD autograding solutions. Graderworks is a Solidworks grading application that has been used to create a web-based grading system [9, 10]. However, this is a closed-source, paid tool. CATIA is another tool designed for use with solidworks [6]. Custom solutions also exist for CREO [11] PLaSM [12] and NX [13].

There is an opportunity to develop an open-source CAD autograding system that allows students to use mastery-based learning. Therefore, the aim of this work was to develop, implement, and evaluate an open-source CAD autograder that utilizes mastery-based learning. An autograder was developed for use with Autodesk Fusion, and it was integrated into PrairieLearn, an open-source mastery-based homework and assessment platform [14]. Surveys following an autograded activity were taken to determine students' perception of the tool and collect feedback for improvements.

Methods

This study was classified as non human subjects research by the University of Illinois Institutional Review Board (#IRB25-1271). All participants in the study gave informed consent.

Autograder Details

In previous versions of this course, students would spend time each week working on a "CAD lab" where they were given a procedure to follow to create various CAD artifacts in Autodesk Fusion. After completing the activity, students would inform a grader that the activity was complete. The grader would then grade the assignment and provide feedback on any mistakes. Altogether, the time range between the assignment being released and students getting feedback on their performance was approximately 1-3 weeks, but could be much higher in some cases. As a result, students often struggled to understand and correct their mistakes, leading to underdeveloped CAD skills in some students.

Our objective in this work was twofold. 1: Reduce the turnaround time so that students are aware of mistakes faster. 2: Enable students to act on this feedback to correct the mistakes that they have made. A key issue to be overcome is that these objectives seem to be opposed. Grading faster requires less time to be allocated to each submission, resulting in lower-quality feedback. Allowing students to resubmit and correct mistakes increased the total amount of grading, meaning feedback will be supplied slower. With an enrollment of several hundred, grading each week's lab activities was a task that took between 27 and 45 collective hours each week, and it was deemed infeasible to hire additional graders to cover a dramatic increase in this effort.

With these constraints in mind, it was determined that the best approach to this problem would be a technological one. If the grading process could be automated, then feedback could be delivered faster, and students could easily resubmit work. However, implementing this sort of technological solution faces several major challenges in terms of correctness, security, and infrastructure.

To address these challenges, we leveraged the Fusion application programming interface (API) which allows users to write code that can interact with the components students create using the Fusion GUI (graphical user interface). Using the API, we extracted key information about each part that a student created. Our goal was to extract enough information to be able to clearly identify if the part that a student has created matches the part they are directed to create in their lab manual. Using a combination of the user inputs and geometrical properties, we have created a set of tests that will identify if a student deviated from the provided instructions.

The next key challenge was to ensure that there were reasonable countermeasures in place to ensure that students were submitting their own work. To do this, we again leveraged the API to extract authorship and edit history information about a part to ensure that the identity of the student who submitted it matched the identity of the student who created the part, and that the part was not shared or imported from another source. We also implemented basic security practices such as encrypting the outputs of the API so that they cannot be edited by students after they are generated.

The final challenge we faced was identifying the infrastructure needed to enable students to submit their work for grading. To address this challenge, we elected to utilize PrairieLearn (PL) [14], which is an open-source mastery learning platform. We selected this platform because it is already in use at our institution, it is designed with the intention of allowing students to submit work multiple times, and because its open-source nature allows us to easily customize it to interface with Fusion.

The overall workflow is as follows:

1. Students open up the lab instructions in PL and follow them.
2. PL generates a unique submission code for each student.
3. Students press a "Grade" button in Fusion and enter their code.
4. Fusion writes an encrypted output file that captures information about the geometry of the part (moment of inertia), part properties (material, units, sketch constraints), and authorship.
5. Students upload the output file to PL and press a "Grade" button, where it is parsed and compared to a known good solution.
6. PL provides students with instant feedback on which tests the part passed and failed (geometry, part properties, or ownership).
7. Students can continue to resubmit until their work is correct, using a new submission code each attempt.

Overall, this workflow allows students to rapidly determine the correctness of their part and make corrections as needed. A block diagram showing this procedure can be seen in Fig. 1. Images of the submission interfaces for both PL and Fusion can be seen in Fig. 2

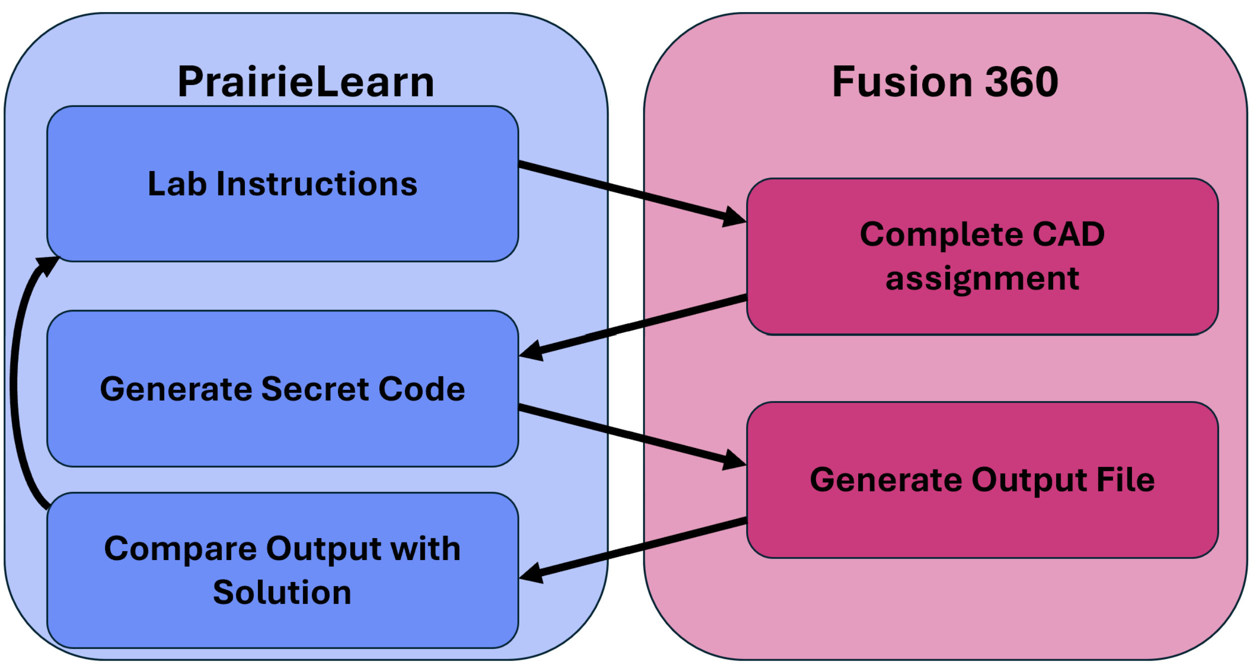

Figure 1: Block Diagram of Autograding Workflow

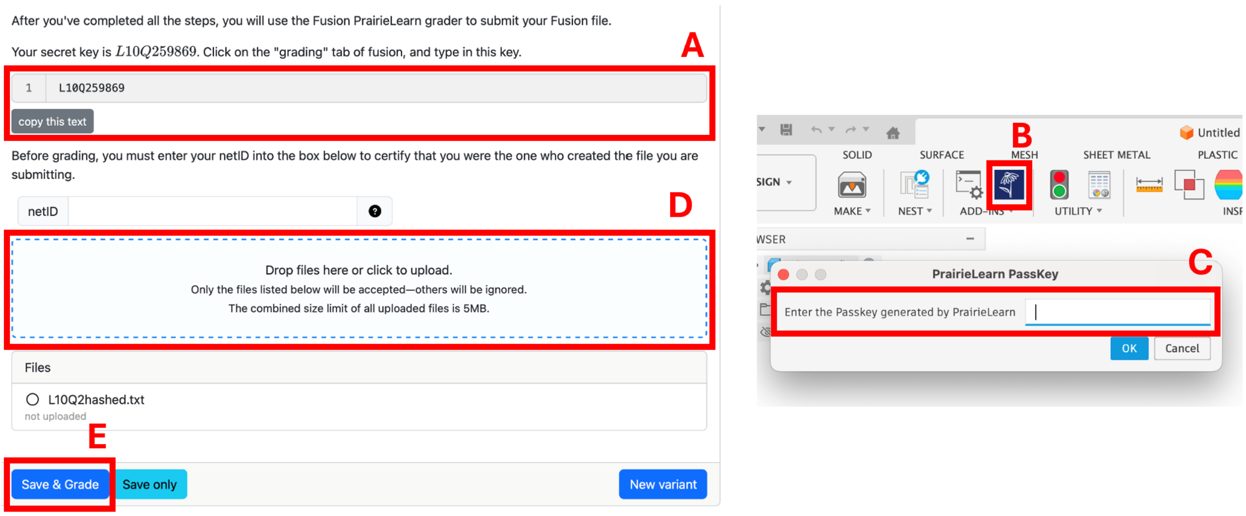

Figure 2: Submission interface in PrairieLearn. A: Submission Code created by PL. B: "Grade" button in Fusion. C: Dialog Box to upload submission code. D: Submission location for output file. E: "Grade" button in PL.

Activity and Assessment

The autograder was piloted in a first-year computer-aided design (CAD) course at the University of Illinois Urbana-Champaign. The course consists of a lecture component (2x per week) and a lab component (1x per week). 328 students were enrolled in Fall 2025. These students are primarily enrolled in Mechanical Engineering (55.2%), with some students enrolled in Engineering Undeclared (23.8%), Engineering Mechanics (11.6%), and other majors (9.4%). This course is primarily focused on learning CAD software via a semester-long design project and weekly CAD labs. Other topics include engineering drawing standards, sketching, the design process, design for manufacturability, and engineering ethics.

Students completed an activity using the autograder during their lab sections. This activity occurred in the 12th week of the semester (out of 16 weeks total), after students had learned CAD

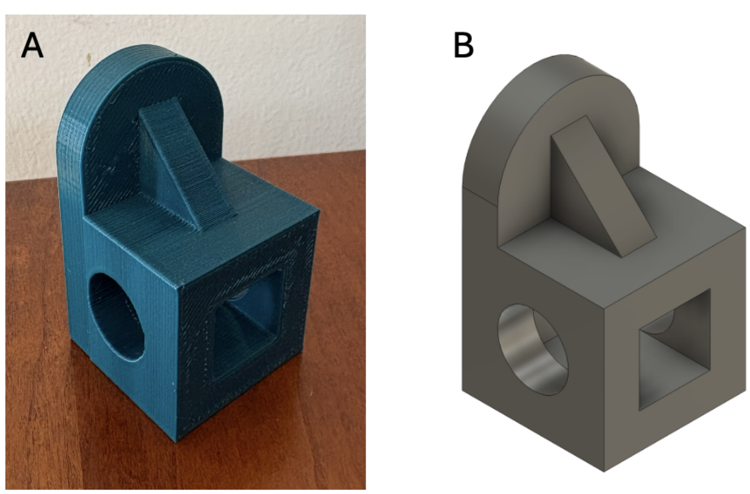

Figure 3: A) Physical part that students measured B) CAD model of physical part

and received manual TA feedback for all previous CAD assignments. In this activity, students first set up the autograder in Fusion on their computer. They were then given a 3D-printed part to take measurements (Fig. 3A), and were tasked with creating a CAD model of the physical 3D-printed part (Fig. 3B).

Students used the autograder to check their part for correctness. The activity was set up so that students could re-submit their work as many times as necessary during the lab section to receive 100% credit.

An optional survey was administered in lab sections following the activity. The survey consisted of 6 five-point Likert-style questions and 4 free-response questions. The Likert-style questions included:

1. How easy was it for you to set up the autograder in Fusion? (Very Easy to Very Difficult)
2. How clear were the instructions for this activity? (Very Clear to Very Unclear)
3. How helpful was the feedback you received from the Autograder compared to traditional grading methods? (much more helpful to much less helpful)
4. How helpful was the speed of the feedback you received from the Autograder compared to traditional grading methods? (much more helpful to much less helpful)
5. To what extent did the ability to resubmit your work until it was correct enhance your learning? (Extremely to Not at all)
6. To what extent did the ability to resubmit your work until it was correct improve your confidence in your CAD abilities? (Extremely to Not at all)

The free response questions consisted of:

1. What did you enjoy about working with the autograder?
2. What about the autograder could be improved for future semesters?
3. Would you have liked more autograded CAD assignments this semester? Why or why not?
4. Room for additional comments.

Survey responses were grouped by Likert questions 1 and 2 (setup questions), Likert questions 3 and 4 (Feedback), and Likert questions 5 and 6 (Learning Outcomes). The qualitative data from Question 3 (“Would you have liked more autograded CAD assignments this semester? Why or why not?”) was grouped into 5 categories: Yes, No, Maybe, I don’t know / No preference, and N/A. Of the students who answered “No”, additional analysis was conducted to determine the reason for answering No. “No” reasons were grouped into 6 categories: (1) students were concerned about ambiguity in grading and how the autograder worked, (2) students felt the assignment structure was unclear, (3) students were concerned the autograder would grade incorrectly, (4) students were not satisfied with the feedback given to them by the autograder, (5) students liked the human interaction from a grader, and (6) no reason was specified. All data were plotted in R (v. 4.4.2).

Results

215 students completed the survey and activity and gave informed consent.

Initial questions about the set up of the autograder and the instructions for the autograder activity revealed that most students found the autograder easy to set up (Fig 4A, 90% specified Very Easy or Easy), and most students found the activity instructions to be clear (38%) or very clear (55%) (Fig. 4B).

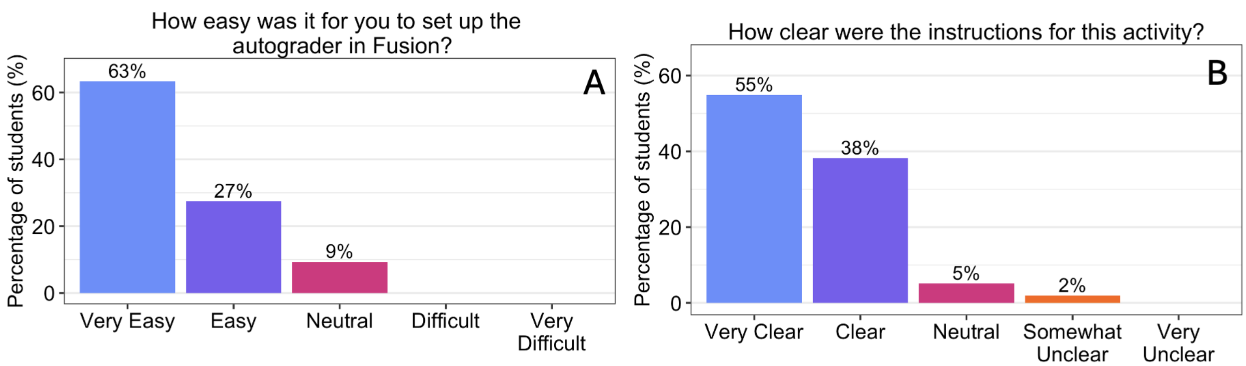

Figure 4: Likert-style questions about Autograder and activity setup (n=215).

Students generally found the feedback from the autograder to be a similar level of helpfulness compared to traditional grading methods (Fig. 5A), but they did find the speed of the feedback to be more helpful, with 87% of students saying that the speed of the feedback was much more or more helpful than traditional grading (Fig. 5B).

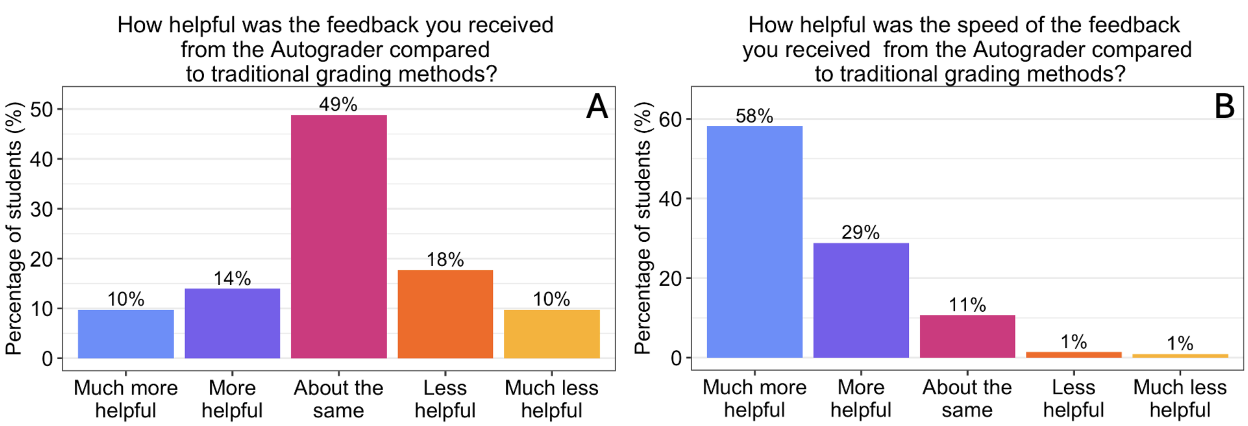

Figure 5: Likert-style questions about the feedback from the Autograder (n=215).

Analysis of the mastery-based nature of the autograder assignment (Likert questions 5 and 6) revealed a majority of students felt that the ability to resubmit their work until it was correct enhanced their learning. 37% and 27% of students noted that their learning was extremely or very much enhanced due to the mastery-based style of the assignment, respectively (Fig. 6A). Similarly, the mastery-based style of the assignment increased student's confidence in their CAD abilities, with 35% noting an extreme increase, 26% noting very much improved, and 24% noting a moderate increase (Fig. 6B).

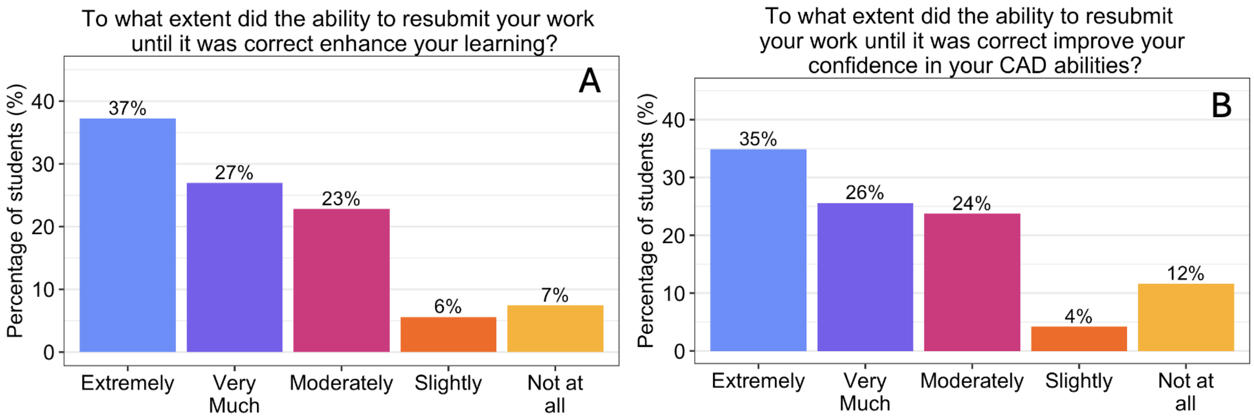

Figure 6: Likert-style questions about learning outcomes from the activity (n=215).

Qualitative data analysis revealed that a majority of students (79%) would have liked more autograded CAD assignments (Fig 7A). The 12% of students who responded "No" mentioned lack of specific feedback as the most common reason they would not like autograded assignments (Fig 7B, 33%), with the second most common reason being a lack of human interaction when the autograder is utilized (25%). Other reasons for not wanting autograded assignments included ambiguity in the grading method (4%), concern over the structure of the autograded assignments (4%), and concern that the autograder could be incorrect (8%). 25% of students who answered "No" did not specify their reasoning.

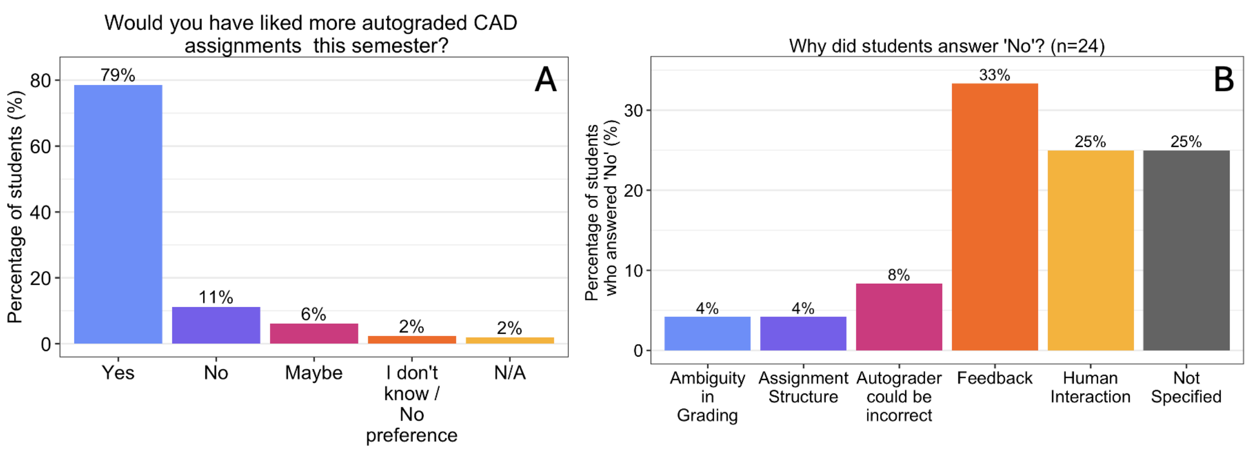

Figure 7: A) Grouped qualitative data analysis (n=215) B) Grouped data of all students who answered "No" to having more autograded assignments (n=24)

Discussion

The autograder was easy to set up for students, and all students were able to complete the activity. In fact, no students thought that installing the autograder was difficult (Fig. 4), which is promising for continuing to expand and implement the autograder in more classes in the future.

Students' thoughts about the feedback provided by the autograder was varied. Most students found the speed of the feedback more helpful than traditional grading methods, which was to be expected.

The average turnaround time for activities in this course is 1-3 weeks, while the autograder provides feedback in seconds. This quick turnaround allows students to correct their mistakes and understand their grades more quickly. On the other hand, the feedback itself was generally regarded to be about the same level of helpfulness compared to feedback from traditional grading. This reaction is expected given that the current feedback from the autograder is a list of which tests the CAD model passed and which tests it failed (e.g. failed geometry test, material test, etc.). In fact, the most common reason for not wanting more autograded assignments was limitations with the feedback that it provided. This has given us a helpful direction for development in the future: more detailed feedback about which features of the model are incorrect could provide better guidance for students as they're learning. Future work will start with a pedagogical analysis of which evaluation metrics and types of feedback are most helpful for mastery of CAD, and will likely involve adding more specific feedback to the autograder.

Data on the student perception of the mastery-based approach to CAD was also encouraging: most students felt that the ability to resubmit their work both enhanced their learning and their confidence in their CAD abilities.

Conclusion

Overall, the response from students regarding the autograder was positive. Students appreciated the quick feedback and the ability to resubmit their work to prove mastery of the material. However, while the speed of the feedback is helpful, the feedback itself could be improved. Future iterations of the autograder will focus on providing more specific feedback to students so they can continue to improve their CAD models and CAD skills.

Especially at large universities, the burden of manually grading CAD assignments traditionally prevents mastery-based learning from being implemented. The CAD autograder developed and evaluated in this paper has potential to allow for scalable, mastery-based learning of CAD that provides instant feedback to students. The open-source nature of the autograder and the learning platform will allow students to use it at no cost to themselves, and will also make it easier for use and adaptation across various universities and applications.

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