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The Impact of Real-Time Additive Manufacturing Feedback and Design Cognition Style on Student CAD Performance

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Work-In-Progress: The Impact of Real-Time Additive Manufacturing Feedback and Design Cognition Style on CAD Performance

Abstract

This Work in Progress study investigates how real time AI generated Additive Manufacturing print time feedback influences student design behavior and how individual design cognition styles interact with this feedback. Students will participate in four CAD-based activities. The AI tool's functionality is tested across four interaction modes: baseline (no AI tool), passive (always visible), voluntary (hidden until clicked), and forced (automatic pop-up with a 2 second design pause). To address the relationship between cognitive style and creativity, participants complete the Cognitive Style Index (CSI). The CSI categorizes problem solvers on a spectrum from Analytic (structured, logical, and incremental improvement) to Intuitive (holistic and immediate sensing of solution). Creative performance is evaluated via a CAD based Alternative Uses Test (AUT) involving furniture assembly. While AUTs typically focus on divergent thinking, this study adapts it to engineering by measuring "uniqueness" through structural characteristics and functional constraints. This research aims to inform the development of adaptive educational tools that cater to diverse cognitive styles, ensuring AI feedback serves as an aid instead of a distraction.

Keywords: CAD, Artificial Intelligence, Cognitive Style Index, Additive Manufacturing, Engineering Design Education

Introduction

Artificial intelligence (AI) tools are becoming increasingly integrated into the engineering design process, particularly within computer aided design (CAD) environments. These tools are intended to support decision making by providing information related to design quality. In educational settings, these tools have the potential to influence how students approach design problems; however, many of the design tools used only provide feedback after the design has been completed [1]. This means that their ability to influence students' real-time design decisions is minimal.

Real-time feedback has the potential to alter how students explore design by making the consequences of design changes immediately visible. For example, immediate information about additive manufacturing (AM), specifically print time, may push students to reconsider geometric complexity or material usage as they work. Despite this potential, there is limited evidence on how students actually engage with real-time AI feedback during CAD based design tasks, particularly when interaction with the tool is optional rather than enforced.

In addition to tool design, individual differences in how students approach design problems may also influence how AI feedback is used. Design cognition style has been shown to affect problem-solving strategies and preferences for structure or novelty [9]. Understanding whether these individual differences interact with AI-based feedback is important to design education tools that can help the largest number of users.

The work-in-progress study presented here examines how real-time feedback about print time influences students' design choices during CAD-based tasks. Specifically, the study compares passive, voluntary, and forced modes of interaction with an AI tool that provides real-time manufacturing feedback. In addition, the study explores the relationship between students' design cognition style and performance on a CAD based creativity task. The goal of this work is to better understand how real-time AI feedback can be integrated into engineering design education to support meaningful student engagement and informed design decision making.

Background

AI Supported Tools in CAD Based Engineering Design

AI and machine learning (ML) techniques are increasingly embedded within CAD and computer aided engineering (CAE) work to support evaluation and optimization of design outcomes. Recent reviews of ML for engineering design highlight the growing role of AI in enabling smart customization, performance estimation, and automated design support within digital design environments [1]. Similarly, surveys of AI in the CAD process describe the use of predictive models and intelligent evaluation tools as a means of augmenting designer decision making rather than fully automating the design process [2], [3].

Within CAD environments, AI based tools are often positioned as decision support systems that provide feedback related to geometry quality or performance metrics [6]. Studies on CAD model comparison and quality assurance further emphasize the importance of quantitative metrics for evaluating design [7]. This further reinforces the legitimacy of using computational feedback as part of the design process. With that in mind, much of the existing work focuses on professional or industrial contexts, with less attention given to how students interact with AI supported tools during educational design tasks.

Feedback Timing and Interaction in Design Tasks

Research on feedback in learning and problem-solving contexts consistently demonstrates that the timing and presentation of feedback has a strong effect. Many education design tools only provide feedback after the task has been completed. This supports reflection but limits opportunities for decision making while the design process is happening. Real-time feedback allows learners to observe the consequences of their actions as they occur, potentially supporting deeper understanding and more iterative exploration of the solution space.

Despite the advantages of real time feedback, its integration into CAD based design tasks presents unique challenges. Design activities require the designers to maintain concentration, meaning interruptions or poorly timed information can lead to a degradation of design quality. Prior work in human computer interaction has shown that enforced interruptions can ensure exposure to information but can also disrupt the cognitive flow [4]. Optional or voluntary interactions allow the users autonomy to remain intact, but it runs the risk of being ignored.

Empirical studies of AI assistance in other professional domains, like legal analysis or medical imaging, further suggest that AI support does not always improve the outcomes [4], [5]. The effects of AI assistance vary depending on the user's skill level and task presented. These findings underscore the importance of examining not only whether AI feedback is available, but also how users engage with the feedback. However, few studies have systematically compared the different modes of interaction with the real time AI feedback in engineering design education, particularly within CAD environments.

Additive Manufacturing Constraints as Design Feedback

Additive manufacturing introduces constraints that influence design decisions. Some examples of these constraints include print time and geometric complexity [6]. Design for AM research has demonstrated that exposure to manufacturing constraints can alter design strategies and encourage production aware thinking [7]. Print time represents an actionable metric that reflects geometric decisions and manufacturability feasibility.

In educational contexts, AM constraints are introduced through instructor feedback or post design analysis. This is an effective method for teaching manufacturability concepts, but it separates constraint evaluation from the act of designing. Embedding and updating AM related feedback directly into the CAD environment has the potential to integrate manufacturing considerations into students' design cognition.

Although prior work has explored AI assisted CAD tools and manufacturing aware design support, there is a limited amount of empirical evidence on how students respond to continuous manufacturing feedback during design tasks. It remains unclear whether students voluntarily prompt real time AM feedback when it is available unforced, and how different interaction modes influence the degree to which this feedback shapes design decisions [6], [7].

Design Cognition and Cognitive Style

Design cognition research has long established that designers differ in how they frame problems and generate solutions [9]. Empirical studies of design activity have shown that cognitive differences influence strategies for adaptation during design tasks. Oxman's work on refinement and adaptation in design cognition further illustrates how designers balance incremental modification with conceptual change when responding to constraints [8].

The CSI framework provides a well-established method for characterizing these individual differences on a range from analytic to intuitive cognitive styles. Analytical individuals tend to favor structure, efficiency, and sequential information processing. Intuitive individuals are more likely to challenge constraints and pursue unconventional solutions [10]. Originally, the Kirton-Adaption-Innovation (KAI) inventory was going to be used as the primary theoretical framework. Using this would not fit into our timeline, so the CSI will be used instead.

Creativity Assessment in CAD-Based Design Tasks

Creativity in engineering design is commonly assessed using divergent thinking frameworks adapted from psychology, like the Alternative Uses Test (AUT), alongside domain specific ideation metrics [11]. Prior work evaluating the validity and reliability of divergent thinking tasks supports their ability to test creative potential, particularly when combined with structured scoring methods [12].

Engineering focused creativity research further emphasizes that creative performance evaluation is related to functional and structural constraints [14]. Comparative studies of creativity measurement approaches highlight differences between social science and engineering perspectives, noting the importance of grounding creativity assessment in task relevant criteria [14]. Metrics for measuring ideation effectiveness provide additional support for evaluating creative outcomes in design tasks that involve tangible artifacts [13].

Recent work has begun to explore creativity assessment within CAD based environments. As CAD tools increasingly incorporate intelligent feedback and decision support, there is a growing need to understand how such tools interact with individual cognitive differences to shape creative outcomes.

Summary and Research Gap

Existing research demonstrates the growing integration of AI into CAD workflows, the importance of feedback timing and interaction design, the influence of manufacturing constraints on design thinking, and the role of cognitive style in shaping design behavior and creativity. However, these strands of research have been examined independently. There is limited empirical evidence investigating how real time AI generated manufacturing feedback influences student design behavior during CAD based tasks, especially when different modes of interaction are employed.

Research Questions

This work in progress study investigates how real-time AI generated additive manufacturing feedback influences student design behavior in CAD based design tasks. The study focuses on how different modes of interaction with this feedback affect engagement and decision making, as well as how individual cognitive differences relate to creative performance. The following research questions guide this work:

- **RQ1:** How does the mode of interaction with real time additive manufacturing feedback (passive, voluntary, or forced) influence students' design behavior during CAD based design tasks?
- **RQ2:** To what extent do students voluntarily engage with real time AI generated manufacturing feedback when access to feedback is optional?
- **RQ3:** How does forced interaction with real time manufacturing feedback affect the temporal relationship between feedback events and subsequent design actions?
- **RQ4:** What is the relationship between students' design cognition style, as measured by the Cognitive Style Index, and creative performance on a CAD based design task?

Methodology

There are five potential activities, in addition to the CSI survey, that participants may complete during the study. There will be an initial instruction section. This is anticipated to be five minutes where the students will read the instructions for their assigned tasks and be allowed to ask questions about what their work is expected to be. After the first five minutes, the students will be free to complete their assigned tasks. After thirty minutes, the students will be asked to complete a separate design task. **Table 1** shows the expected study plan.

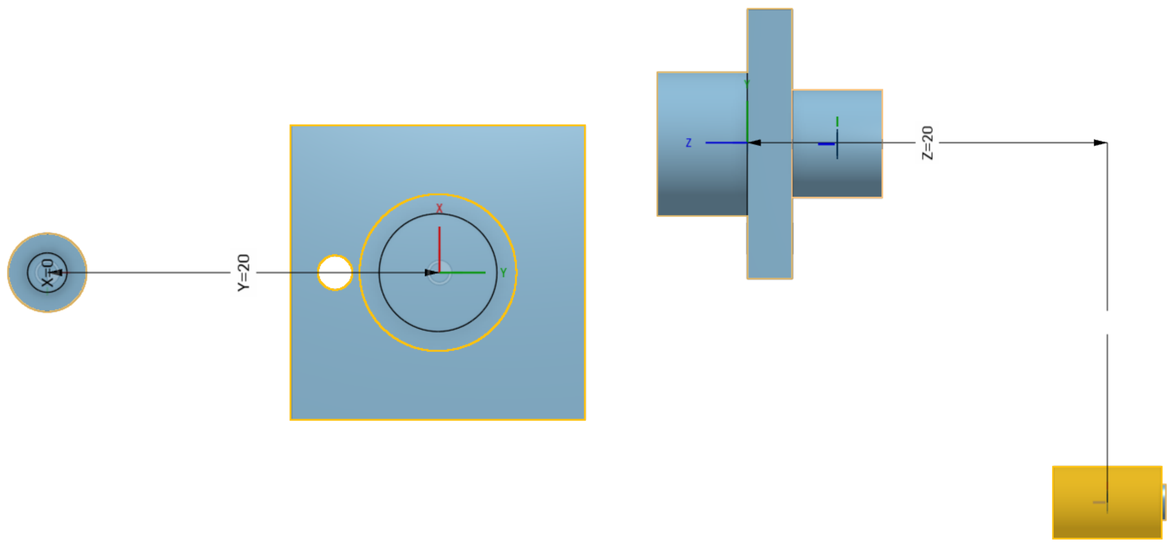
Table 1: Study Plan

Time	Section 1	Section 2	Section 3	Section 4
5	Instructions	Instructions	Instructions	Instructions
35	Forced | Baseline	Passive | Voluntary	Baseline | Passive	Baseline | Passive
35	CSI | Voluntary	Forced | CSI	Forced |Voluntary	CSI
ONL	CSI Survey	CSI Survey	CSI Survey	CSI Survey

Note that after the instructions, the sections will be split into two groups with each being assigned a different activity. Additionally, "CSI" in this table refers not to the CSI survey instrument but a different activity which is described later in Design Challenge 5.

Design Challenge 1 - Baseline

The first of the activities is the Baseline activity. There will be no AI assistance as this challenge is purely to observe normal design behavior and set a baseline skill level. The CAD task structure will remain the same for four out of the five activities. The participants will be asked to design a connector component between two parts. The parts that the students will be asked to connect in the Baseline Group are shown in **Figure 1.**



(a) Top View *(b) Side View*

Figure 1: Connection Piece for Baseline Group

The connector piece must meet a predefined manufacturing time threshold and be functional. The manufacturing time threshold will be the same for all participants in each activity. This threshold is selected because it will be restrictive enough to have design tradeoffs but will still allow for multiple viable solutions. An additional constraint placed on the participants is that they must use at least one of the grooves or pegs present in the geometry of the given parts

Design Challenge 2 – Passive

The participants in this group will complete the same task as the participants completing Design Challenge 1. As shown in **Figure 2**, manufacturing-time feedback is generated by the AI tool and is continuously visible in the corner of the interface and updates in real time as the design geometry changes. Participants are not required to interact with the tool and no prompts, alerts, or interruptions are presented. This design challenge serves to capture participants' natural design behavior under passive exposure to AI-generated feedback.

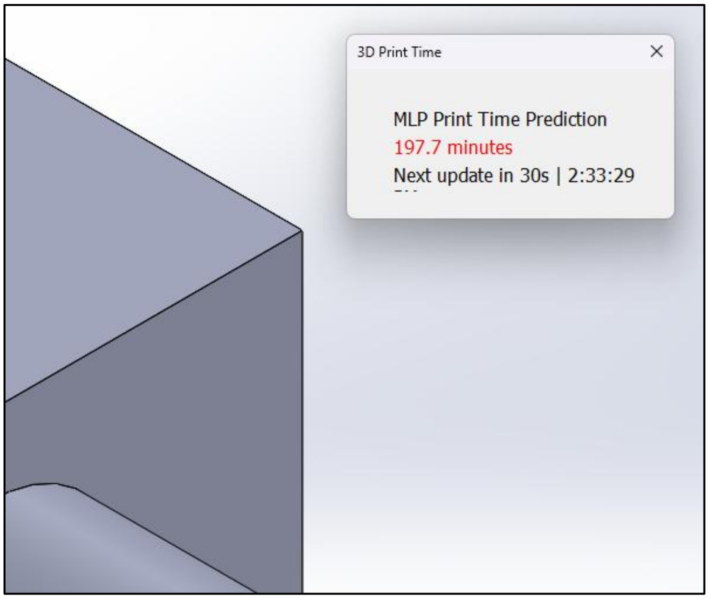
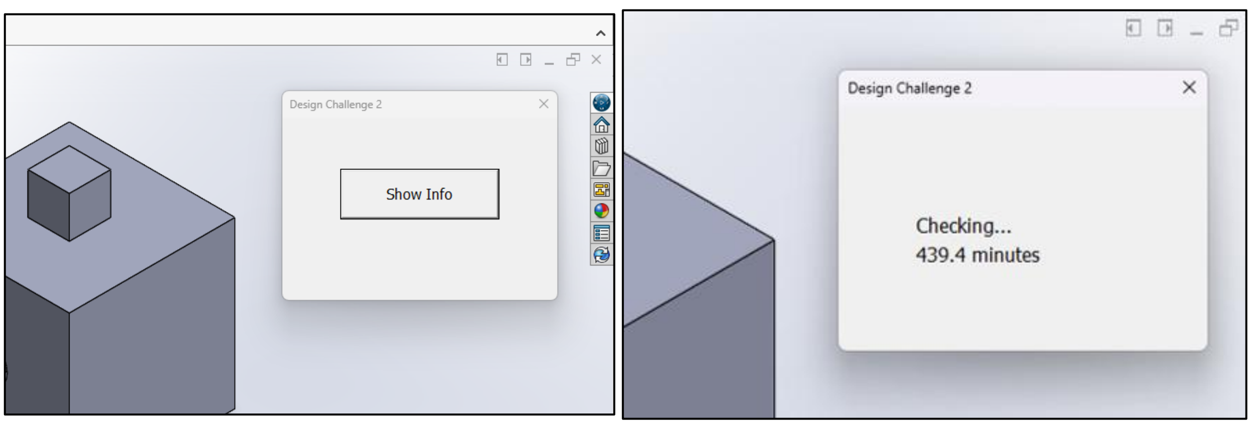


Figure 2: Interface for Design Challenge 2

Design Challenge 3 - Voluntary

The difference between this challenge and the baseline challenge is the mode of interaction with the AI tool. In the voluntary interaction group, the manufacturing time feedback is hidden by default. Participants may reveal the information by clicking a button in the corner of the interface. This interaction is optional and can be clicked on at any time while designing. This condition forces the students to actively seek out AI feedback rather than passively observe it. An example interface that this group of students will see is shown in **Figure 3**.



(a) Before *(b) After*

Figure 3: Interface for the Voluntary Group Before and After Information is Shown

Design Challenge 4- Forced

In the forced interaction group, manufacturing time feedback is automatically displayed whenever a significant change is detected. A significant change is defined as at least 20% variation in estimated manufacturing time relative to the participant's previous design state. When triggered, a popup displaying the updated manufacturing time estimate appears and disables further design actions for two seconds. This pause ensures that the participant sees the information before resuming the task. After the two second interval, the interface returns to the normal design screen. The example of how the interface looks is shown in **Figure 4**.

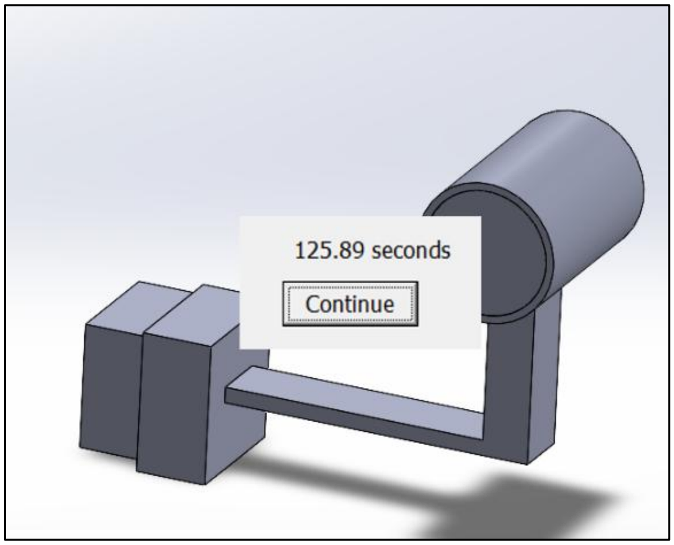


Figure 4: Interface for the Forced Interaction Group

Design Challenge 5 - CSI

The fifth design challenge is independent from the first four design challenges. Participants are provided with a collection of geometric shapes and asked to assemble them into a piece of furniture. Furniture was selected because it is a familiar object that does not need outside knowledge. Examples of the available shapes are shown in **Figure 5**, along with examples of furniture created with combinations of those shapes.

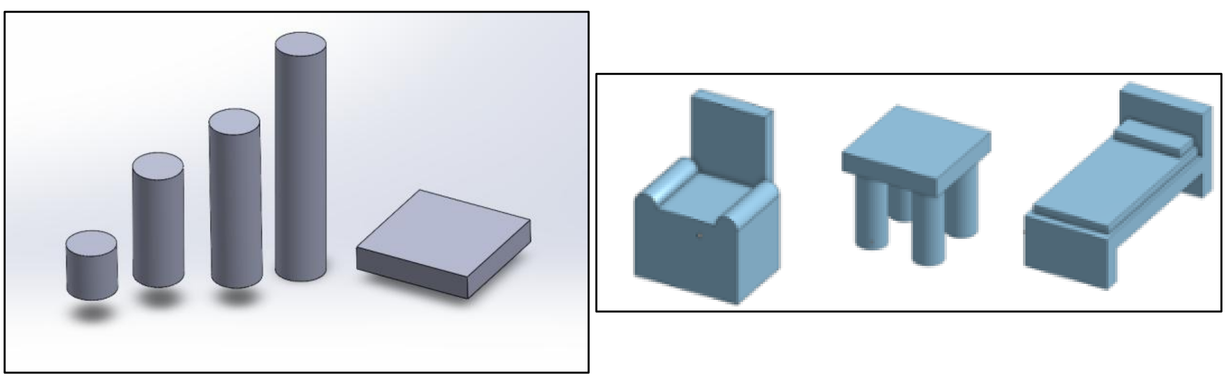


Figure 5: Examples of available shapes and potential combinations

Participants can freely combine the provided components without constraints on anything. The resulting assemblies will be evaluated using a "uniqueness" score. This will be a five-point scale and is computed based on the structural characteristics of the assembly and number of similar designs from all participants.

To illustrate the "uniqueness" score, an example is provided. If one participant creates a lamp, and they are the only one to do so, then that is a unique idea and will score higher. If fifty participants design a stool, then that is not a unique idea; however, if one participant designs a stool out of fifteen parts, then that is more unique. This scoring approach is loosely derived from Shah's work on ideation scoring metrics [13].

Survey

After completing all the design challenges, participants will be asked to complete an online survey. The survey consists of two sections. The first section is the Cognitive Style Index (CSI) which is used to characterize participants' cognitive design styles along the Analytic - Intuitive spectrum. The second section collects background and perception data, including participants' prior CAD experience, self-reported skill level, and attitudes toward the AI tool and its usefulness while doing the tasks. These responses will be used to give more information about the observed design behaviors.

Expected Results

As this study is currently undergoing review by the Institutional Review Board (IRB), the following section outlines how the data collected will be analyzed and the expected outcomes of the proposed experiment.

Design Challenge 1 is intended to establish a baseline for participants' design behavior. The data collected to illustrate normal design behavior includes the total modeling time, the number of features, and the final design. The results from this challenge will serve as a reference point for behavior observed during the design challenges that contain the AI tool.

Design Challenge 2 is intended to establish a baseline for participants' design behavior with real-time feedback when that information is only available through the passive visual display. Since participants are not required to interact with the AI tool, the expectation is that there will be little direct engagement with the tool, and the design decisions that are seen reflect participants' existing CAD habits and prior experience. The data collected for analysis for this design challenge will be the same as the data collected for the first design challenge. The results from this challenge will serve as a reference point for behavior observed in more interactive feedback conditions.

Design Challenges 3 and 4 are expected to provide insight into how different interaction modes influence whether AI feedback becomes an active part of the design process. In the forced interaction condition, we expect clear evidence of AI influence, as participants are required to observe the time changes. This condition is anticipated to produce observable coupling between feedback events and subsequent design actions. In the voluntary interaction condition, expected outcomes are less certain and are a central research question of the study. If the real time AI feedback is naturally integrated into students' design cognition, participants in this condition are expected to access the tool multiple times and demonstrate design changes that correlate with feedback information. Alternatively, limited voluntary engagement would suggest that real time feedback alone might be insufficient to influence design behavior. These two design challenges will have some additional data that needs to be collected for proper analysis. Additional data from Design Challenge 3 and 4 will be the number of times that the tool is accessed, when in the design process the tool was accessed, the amount of time between the feedback appearing, and the next modification made to the part.

Design Challenge 5 is expected to reveal relationships between design cognition style and creative performance in a CAD-based Alternative Uses Test. The expectation is that participants with more Intuitive cognitive styles may produce designs with higher uniqueness scores, while more Analytic participants may generate designs that are more conventional.

Collectively, these expected results will help clarify when and how real-time AI feedback influences student design behavior, as well as how individual cognitive differences relate to creative outcomes in a CAD-environment.

Limitations

A limitation in this study is that the only information in terms of additive manufacturing feedback that is being provided to the students is the print time for the part that they are designing. This is just the first iteration of this design tool, and additional parameters may be given to provide more relevant feedback.

Conclusion

This work in progress study tests four different modes of interaction and their effect on the design process. These include a baseline, passive, voluntary, and forced approaches of presenting feedback. Moreover, the effect of design cognition style (Analytic vs Intuitive) on a CAD-based Alternative Uses Test are also investigated. The next steps are to get IRB approval, collect data, and analyze and interpret the result.

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