Development of a Novel Computer-Aided Design Experiment Protocol for Studying Designer Behaviours

by

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Abstract

Computer-Aided Design (CAD) is indispensable for modern engineering endeavors. The craft of creating CAD models requires extensive experience and expertise. Unfortunately, most traditional CAD training remain focused on declarative knowledge and not higher-level thinking. Studying expert usage could provide insights into the elements of effective CAD modelling.

As the first step towards decoding CAD expertise, a novel experimental protocol was developed to capture and characterize designer actions during modeling. The study will serve as a foundation for future CAD design research. The protocol was tested with an experiment of 19 participants of varying skill levels. Event plot visualizations and hidden Markov Models revealed differences between two groups of performance-segmented participants, with the experts adopting a more consistent and organized modelling approach.

Compared to existing methodologies, the automated processes developed for this study leverages automatic data collection and analysis to significantly reduce the time and effort required to perform design experiments.

Acknowledgments

First and foremost, I would like to express my gratitude for my supervisor Dr. Alison Olechowski. My graduate school journey has been nothing like what I had envisioned initially, and it would not be an overstatement to say that it has completely changed the trajectory of my life and career forever. This journey has taken many twists and turns, but I am thankful that you were there with me every step of the way, offering your support, guidance, and unwavering belief in me.

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Lastly and most importantly, I wish to thank my family for always supporting me and believing in me, and for all the sacrifices you have made. Even though we are far apart, I know I am always on your minds and in your hearts.

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1 Introduction

1.1 Computer-Aided Design

Since their inception in the mid-1960s, Computer-aided Design (CAD) programs have continually evolved and expanded in terms of capabilities. Today, they are indispensable for nearly all modern engineering endeavors. Almost every single product we use and interact with daily has had at least some part of it designed using a CAD software.

CAD systems now play a central role in the entire product life cycle. Entire assemblies can be conceptualized, modelled, simulated, and prototyped virtually, often without requiring any physical resources. Hundreds of design iterations and simulations could be performed to achieve design requirements without generating any scrap. With the help of CAD, engineers today can design products that are more complex and at a faster rate than ever before.

The ability to be able to use CAD effectively is now considered a fundamental skill in many fields of engineering and design. A cursory search will reveal that the vast majority of job postings in fields such as mechanical, manufacturing, or aerospace engineering include some form of CAD knowledge as a requirement.

1.2 First Step in Improving CAD Education

Unsurprisingly, CAD training has been now included in engineering curricula at the undergraduate level for many years. Increasingly, it is also being taught to students at the grade school level. However, while CAD systems have continued to experience technological innovations and advancements, the development of CAD education and training seems to have followed a much slower trajectory.

Scholars and researchers have proposed best practices and guidelines for CAD modelling [1]–[4]. These frameworks provide systematic approaches that help narrow the solution space and create models that are more stable and better at capturing design intent. However, effective CAD modelling still requires extensive experience and expertise. Multiple paths are typically available for any desired geometry. The difficulty lies in selecting the option that best captures the design intent while also balancing an array of other requirements such as model flexibility, efficiency, and parametricity. Unsurprisingly, true mastery of CAD modelling takes many months, if not years, given the complexity of the CAD systems today and cognitive challenge associated with creating high quality CAD models. Unfortunately, most traditional CAD training has remained focused on teaching declarative knowledge and not higher-level thinking.

Rynne et al. have shown in their study that even students with extensive experience and prior CAD training were still unable make strategic CAD modelling decisions and often fixated on their initial flawed modelling approach instead of attempting alternative approaches [5]. Many users may be well-versed in operating CAD programs to accomplish individual tasks but still face significant challenges when combining multiple features cohesively to create complex CAD models if they are unable to transfer their existing knowledge across different contexts.

To tackle the challenge of training well-rounded CAD users, we can look to the existing body of knowledge that is embedded within the large group of expert CAD users who have accumulated countless hours of combined CAD experience. Studying existing CAD experts' actions and thoughts while they model could be an effective way to extract procedural knowledge. Doing so could provide an opportunity to codify and extract procedural knowledge in context.

The first step towards extracting procedural knowledge is a way to reliably record and analyze expert CAD user's actions as well as capture their thought process during modelling. This paper details the development of a new method to achieve that goal. A methodology to record expert CAD usage in an efficient manner will serve as the basis for future research that further uncovers insights into the elements of effective CAD modelling.

1.3 Objectives and Contributions

The main objectives and contributions of this project include the following:

- Establishment of a novel method to conduct CAD design experiments virtually
- Evaluation of the experimental protocols to inform future studies
- Design of a CAD experimental task suitable for a wide range of participants
- Development of an automated method to extract CAD user actions through data mining
- Visualization and characterization of CAD designer activities through hidden Markov models and event plots
- Identification of modelling strategies utilized by proficient CAD users

2 Background and Literature Review

2.1 CAD Knowledge and Training

CAD knowledge can be separated into two categories: declarative and procedural. Declarative knowledge is the knowledge of the commands and algorithms available within CAD systems [6]. It is the form of knowledge most often taught in CAD training courses and written in training manuals. Learning declarative knowledge is akin to learning vocabulary before learning to write prose. The user is introduced to the functionalities that exist within a CAD system and shown the sequence of operations necessary to perform specific tasks. A basic example of declarative knowledge is knowing which specific icon to click in CAD to add a circle during sketching, as well as knowing that one must click and drag the mouse to control the size of the circle during creation. Declarative knowledge can tell someone *how* to do a specific operation but does not provide insight into *why* that operation should be performed or whether another option would be more preferrable instead.

Procedural knowledge is knowing what strategies to employ to achieve a certain goal and why certain solutions are more favorable compared to others [7]. It allows a CAD user to know when to use a certain feature given the current situation and understand why it is advantageous. Continuing the analogy from before, procedural knowledge is the knowledge of picking the right words to string together to create coherent sentences and paragraphs that convey meaning. Just as writing is more than simply integrating words and sentences, complex modelling also often includes an element of style. Expert modelers can convey meaning and intent through their specific modelling actions and strategic decisions. As Hamade et al. have shown, procedural knowledge takes time to develop and is highly cognitive in nature [8]. Unsurprisingly, this is the aspect that novice CAD users typically exhibit a weakness in [9].

Both forms of knowledge are critical for effective CAD modelling, but logically, one must first develop a solid foundation of declarative knowledge before attempting to develop procedural knowledge. This explains why CAD training typically begins with teaching declarative knowledge, such as the sequences of actions required to perform specific actions within the CAD system. Unfortunately, most courses do not then advance to provide training on procedural knowledge. As Chester lamented in his paper, *"the didactic approach is still the dominant* *pedagogy in both education and Industry*" [7]. While researchers have been searching for ways to incorporate more procedural knowledge into training curricula, most CAD training today continues to fall short on that front [10].

Design experiments focused on studying CAD user activity provide an interesting mechanism for extracting procedural knowledge exhibited by designers [6]. Instead of engaging in the monumental task of developing a compendium of procedural knowledge, studying expert CAD practitioners could yield procedural knowledge that are more valuable and applicable.

2.2 Existing Literature on CAD Design Experiments

2.2.1 Common Solutions for Studying Designer Actions

The difficulty in recording CAD designer actions is a challenge faced by many researchers interested in studying designer behavior and decision making. In general, three approaches have been developed, each with different benefits and drawbacks.

The first approach is by creating fully custom software to allow for maximum flexibility and coverage during data collection. To study designer actions, Rahman et al. developed a CAD based research platform from the ground up called *ENERGY3D*. It is a simplified CAD platform purpose-built to allow researchers to observe the behaviours and actions of participants as they work on design challenges [11]. The platform has built-in functionalities capable of recording designer activities in fine detail, which is extremely useful for studying designer behaviors. However, the platform is limited to one type of design activity and has limited extensibility.

Other researchers have opted to utilize standard CAD systems such as SolidWorks, AutoDesk Inventor or Solid Edge and leverage custom scripts for data logging purposes [9][12][13], although this approach comes with more limitations on what data can be collected, as most commercial CAD solutions were not created with design research in mind. The benefit of this approach is that study participants are using the CAD systems commonly used in industry, making the experimental findings more applicable to real-life scenarios.

Another common method for studying and analyzing designer actions is through audio or video recording and manual coding, as is done in Atman et al. [14], Buckley et al. [15], and Ozturk et al.'s studies[16]. This method can provide very high resolution and flexibility; however it is also time and labor intensive, as well as requires multiple coders to ensure intercoder reliability.

2.2.2 CAD User Traits and Attributes

The traits and attributes of designers and CAD learners is a richly explored topic. The aim is to better understand how different individuals learn and process information when using and learning CAD, then use that knowledge to improve educational efforts and training curricula.

From Hamade et al.'s study on desirable attributes for CAD trainees, we find that the ideal CAD learner is an individual who is technically competent, motivated, and perceptive. Individuals who has an active, sensor, visual, and sequential learning style are also considered to be at an advantage when learning CAD [17].

Spatial ability is another often-studied attribute shown to have a strong influence on one's ability to gain proficiency in 3D CAD. Hamlin et al. concluded from their study with undergraduate students that spatial ability does indeed significantly impact one's ability to learn and use 3D CAD software [18]. This result is corroborated by research carried out by Branoff et al., Delahunty et al., and Kösa et al. [19] [20] [21].

Interestingly, merely using 3D CAD software was not shown to be particularly effective for developing spatial reasoning [22]. This suggests that a thorough training program should involve more than instructions and exercises limited to CAD. Thankfully, research shows that carefully designed courses can be effective in helping students develop their 3D spatial skills [23].

With better understanding of how individual attributes affect the learning process for difference users, CAD training programs could be personalized to suit different styles of learning and improve the rate of skill uptake for novice CAD users. Research suggests that careful cultivation and targeted instructions can yield substantial benefits, even for students who start at a perceived disadvantage. Better tools and methods for collecting and analyzing designer actions will be crucial for educators looking to evaluate and develop novel training programs.

2.2.3 CAD Designer Actions

Similar to designer traits and attributes, the actions of CAD users during engineering design and problem solving have also been studied extensively. Often, differences between expert practitioners and novice users are analyzed to identify opportunities for improving the training and education in design related activities.

Gopsill et al. collected and analyzed the actions of undergraduate mechanical engineering students in AutoDesk Inventor to gauge their level of proficiency at utilizing the software [12]. Similarly, in the analysis of their design experiments, Xie et al. put forward metrics for measuring designer actions, such as calculating the ratio of creation to revising actions to infer how reflective the designer is during modelling [24].

McComb et al. conducted a series of studies by recording designer actions while working on configuration design problems and analyzing their design operation sequences through Markov chains and hidden Markov models as a way to extract hidden insights within their action sequences [25][26][27].

In Bhavani et al.'s study using 2D CAD, the actions of groups with different experience levels were analyzed to explain the differences in the quality of their final models. It was found that high CAD experience users used a larger variety of commands and novice CAD users tended to delete elements instead of editing them [28].

By comparing practicing engineers and students working on the same CAD modelling task, Ozturk et al. concluded that the engineers with more adaptive expertise are able to model more efficiently and accurately [16].

Similarly, Atman et al. compared the engineering design processes between expert practitioners and students and discovered significant differences between the two groups. Experts spent significantly more time searching for solutions, gathered more information, maintained a larger solution space, and followed a more consistent pattern [14].

2.2.4 Evidence of Inadequate CAD Training

As discussed in Section 2.1, current CAD education curricula has been viewed by many as lacking. Several studies provide supporting evidence for this perspective. In a study assessing mechanical engineering undergraduates' conceptual knowledge in three-dimensional CAD, Daud et al. found that students have a weak understanding of the core concepts of 3D CAD [29]. Delahunty et al. similarly found many students' modelling capabilities to be severely deficient [20]. Clearly, CAD education has room for improvement.

3 Experimental Design

3.1 Overview

We recruited a group of CAD users with varying experience levels to participate in our research experiment, where we asked each participant to work on two prescribed modelling tasks following a set of drawings. The entirety of the study was conducted remotely. We leveraged Onshape's cloud CAD capabilities for the experiment CAD modelling task and web conferencing (Zoom) for screen sharing and video calling. We also collected demographic information and self-identified CAD skill level for each participant through pre-study surveys administered using Qualtrics.

The first experimental task involves participants making a 3D CAD model following a set of detailed engineering drawings. The modelling task was designed to test each participant's CAD abilities. In the second experimental task, we asked the participants to make a series of changes to the models they created in the first task. This was motivated by previous research showing the importance of model modification as part of the CAD learning process, as it provides an opportunity for self-assessment [10][30][31].

The following sections outline the design goals of our experiment, the various design configurations explored, as well as details of the final experimental tasks given to all study participants.

3.2 Common CAD Usage Scenarios

For the experiment to yield useful results and insights, the tasks given to participants during the experiment need to serve as good analogues of the types of work that are performed in industry. Note that for the purposes of this study, we chose to focus specifically on part modeling, since it is one of the most fundamental aspects of CAD usage and serves as the basis for most of the more complex CAD activities such as assembly modelling, surface modelling, engineering drawing creation, or finite element analyses (FEA).

We start by looking at a few common scenarios of CAD usage in industry:

- *Development of brand-new designs with CAD*

  This often occurs during the early phases for new initiatives and products but could also regularly happen in ongoing projects wherever there is the need for new a component. Conceptual sketches and diagrams may be available from the problem definition phase, along with specifications on key interfaces for parts that need to mate to other components. Concepts created by industrial designers may also be available to specify a physical boundary that the CAD designers need to work within. Depending on the design phase and end goal, the CAD user might work on detailed part design or simple conceptual models.

- *Modification of an existing product/part in CAD*
  This is another common use case for CAD in engineering design. Designs regularly go through iterations and revisions in response to design improvements, requirement changes, customer request, field failures, and more. In large engineering teams, it is not uncommon for someone to make modifications to CAD models created by another engineer in the company. In the event that the original designer is no longer available to be consulted, successful inference of design intent and model structure becomes extremely crucial.

- *Recreation of an existing item in CAD*
  In certain instances, existing physical objects may have to be recreated in CAD. There may be components whose CAD models are lost, corrupt, or no longer compatible after CAD system migrations. Parts made through manual processes or created by third parties often do not have readily available CAD models. Competitor components used during benchmarking typically would not come with CAD models either. All of these scenarios could require recreation of existing parts in CAD, potentially with the help of advanced techniques such as high-resolution 3D scanning.

- *Building models for simulations*
  The wide range of computer-aided simulations such as FEA, CFD, plastic injection molding, generative design, or more specialized simulations sometimes require purpose-built digital models to be created.

3.3 Experimental Design Goals

We strove to fully replicate one or more of the previously described common CAD use cases in our research experiment while working within the constraints of designing and conducting realistic experiments.

In our case, given the COVID-19 restrictions, we had to design the experiment to be fully remote and virtual. Past CAD studies carried out by the research lab were conducted in-person, which had the benefit of easily controllable environmental variables. With the majority of students attending school remotely and full-time workers working from home, many of the typical participant recruitment methods were not viable. In order to account for all the perceived potential complications, we decided to develop the experiment protocol to be as straightforward as possible and maintain only a moderate level of experimental task complexity.

The following outlines a list of goals and requirements developed for the design of the experimental task:

- The experimental task difficulty should be appropriate for a wide range of skill levels
- The task should incorporate opportunities to include “smart” modelling strategies, such as identifying and leveraging symmetry, or mirror and patterned features
- The instructions should be straightforward and easily comprehended by all participants
- The task should be designed to provide a way to score and compare participants as easily and objectively as possible
- The experimental task should be open-ended enough to allow for multiple solutions
- Trivial and time-consuming tasks should be minimized (such as filleting a large number of edges or adding minor cosmetic finishing details in CAD)
- The total experiment duration should be between 60 - 90 minutes, to maximize user recruitment and participation

3.4 Experimental Tasks Explored

A range of potential experimental tasks were considered, each with their respective pros and cons. Complete explanations and details for tasks that were discarded are available in Appendix A. For the sake of brevity, here we will only briefly describe each to provide some context for the evolution of the experimental design. The hope is that future researchers can draw inspiration from the concepts and improve upon them in future studies. Wherever possible, beneficial aspects of the abandoned tasks were incorporated into the final experimental task design, which is detailed in Section 3.6.

1. *Make design changes on a pre-made CAD model of a jig:*
   Designed to mimic the common workflow where one makes changes to a model made by another person. The goal is to observe how people break down an existing model mentally and infer design intent. It was determined to be too difficult to control the scope (maintaining design freedom while still allowing the participant models to be comparable on a common standard). Another challenge was accounting for how participants may be affected by the particular modelling style used to create the provided model.

2. *Recreate 3D rendered object in CAD:*
   An attempt to virtually recreate observing and measuring a real-life item then recreating it in CAD, such as providing a person with a widget and a pair of calipers. This approach was deemed too awkward and unnatural after testing.

3. *Model an item of the participant's choosing*
   Participants select their own objects to model during the experiment. Challenges arise when trying to maintain a consistent level of model complexity and difficulty.

4. *Speed CAD*
   Series of tasks where participants aim to create CAD models as fast as possible based on drawings. We decided against the idea since we wanted to focus on modelling behaviour that reflect participants' typical CAD usage, whereas adding a high level of time constraint will likely encourage users to rush and seek out shortcuts, defeating our goal.

3.5 Pilot Testing

The experimental tasks and procedures were tested with the help of other members in the research lab. The results and their feedback were used to make improvements and validated with subsequent iterations.

Once the experimental tasks were developed to an adequate level of maturity, and the full experimental flow was determined, a full package was presented to the Research Ethics Board (REB) for approval.

After obtaining ethics approval from the REB at the University of Toronto, two full pilot runs were conducted to confirm the flow of the entire study from start to finish, as well as highlight any necessary adjustments to both the experiment timing and the experimental tasks, before officially conducting the study with recruited participants.

All participant data are anonymized, and only coded participant IDs will be used for any individual references presented in this thesis.

3.6 Recruitment

Official recruitment began after REB approval of the experiment procedures.

A message outlining the purpose, experimental tasks, eligibility guidelines, and a link to an online Qualtrics interest form was shared with a wide range of potential participants, including the users on the Onshape User Forum, second year mechanical engineering students at the University of Toronto, students who participated in a CAD design course at the Memorial University of Newfoundland, as well as CAD users at PTC, the Parent company of Onshape.

Participants were compensated at a rate of $15/hour, as a token of appreciation for their participation. At the request of PTC, employees of Onshape participated on a voluntary basis and received no compensation.

The full recruitment process for the study is shown in Figure 1:

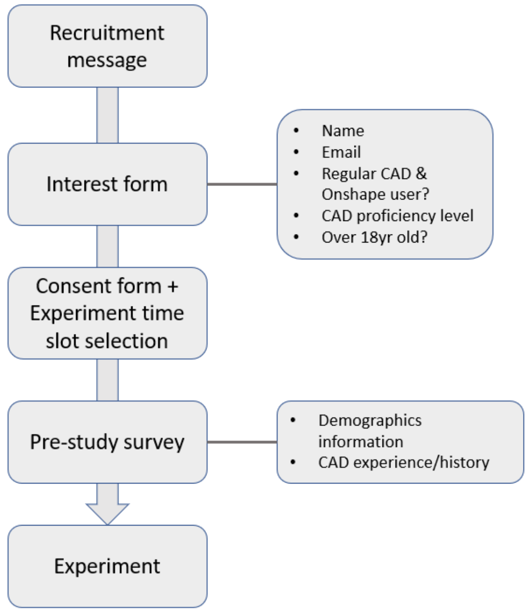


Figure 1 Recruitment Process Leading up to Experiment

3.6.1 Participant Recruitment Targets

We selected individuals based on a number of criteria. First, they must have used any CAD program for at least 12 months on a consistent basis. Since we are using Onshape as the CAD software for the experiment, we also looked for participants with more than half a year of Onshape specific CAD experience to ensure recruited participants would have sufficient proficiency in Onshape and could perform above a minimum level. This was done to ensure the experiment would capture enough datapoints and not capture unfamiliar users spending a significant amount of time exploring and learning to use the CAD software. Since actions during sketch creation and model parameter definition are not captured in our dataset, a novice user who spends most the time defining sketches, such as drawing sketch geometries and placing constraints, would generate very few datapoints. As such, we only recruited participants who self-reported having CAD experience levels as “Intermediate” or “Expert” (definitions for each are in section 3.7). Participants who self-selected as intermediate or expert but listed little CAD experience (having only used CAD for a few months, for example) were asked to provide additional details of their modelling experience to ensure they meet the minimum requirement.

3.7 CAD Experience Determination

Determination of CAD skill level was a challenging task. While most large CAD software vendors have certification programs such as the Onshape, SolidWorks, or Audodesk Certification Exams, many CAD users do not complete them either due to their high costs or lack of perceived value. This is especially likely with students or designers who work at smaller firms that do not have the budget to enroll all their employees in certification programs.

We decided to tackle this problem with a two-pronged approach. In the interest form, we asked participants to self-identify their CAD ability level based on a 3-tier system. Detailed descriptions were included for each to provide context and clarity. The levels and the descriptions shown to participants are as follows:

- *Novice*: I understand the basics of CAD, have made a few simple parts and followed some CAD tutorials. I have used CAD for course labs/personal projects/team projects
- *Intermediate*: I am comfortable making medium to high complexity parts that include multiple sketches, datums, and features. I have used CAD for personal and/or team projects and made meaningful contributions to the models
- *Expert*: I have extensive experience using CAD in a professional setting or teaching CAD to students, with a good mastery of CAD principles and regularly work with large CAD models with complex geometries/assemblies and large feature-counts

Initially, a short pre-study test involving a series of prescribed modelling tasks was planned to assess each participant’s CAD competency more concretely but was eventually removed due to time constraints and the assumption that only accepting participants who meet the minimum experience threshold would be sufficient.

3.8 Experimental Tasks in Detail

The following sections detail the experiment once a participant reaches the “Experiment” bubble shown in Figure 1.

3.8.1 Experiment Flow

The overall flow and sequence of events of the experiment is shown below in Figure 2. The experiment first starts with an introduction presentation, where the overall experiment flow is explained to the participant, along with context for the study. The instructions for the two experimental tasks are also discussed during this time. The full duration of the study was planned to be 90 minutes.

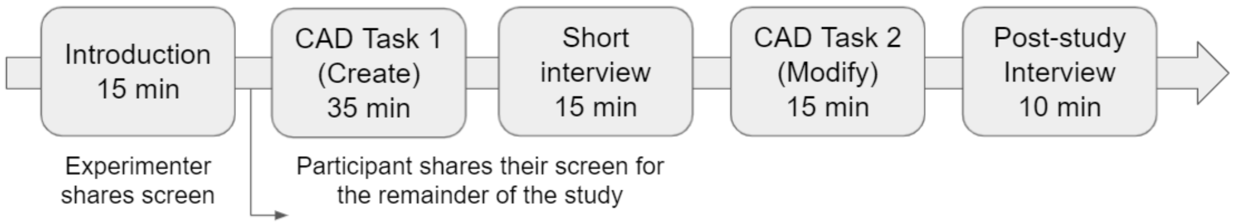


Figure 2 Experimental Flow

During the introduction presentation, participants were repeatedly told to not rush through the tasks and maintain high standards and follow their typical workflow. For CAD Task 1, participants received a verbal cue when ten minutes remained, and five minutes for Task 2. The cues were intentionally kept to a minimum as to minimizing adding pressure and encouraging participants to rush.

3.8.2 Participant Files Management

A new Onshape account was created within the Ready Lab enterprise Onshape server specifically for the study. Its file access was controlled so only specific files shared with the account would be available. Prior to every study session, that Onshape account's password would be changed and shared with the participant. The participants were encouraged to personalize the Onshape interface settings such as navigation options and keyboard shortcuts to match their preferences. There is little risk in allowing participants to log in prior to the study without supervision since the account has no direct access to any files, essentially serving as a sandbox environment.

A separate Onshape document was created for each participant with the experimental task instructions pre-loaded into it and the document name labeled with the coded participant ID. This helps ensure all participant data could be easily tracked and managed before and after the study. The Onshape document is shared with the experiment Onshape account during the study, and subsequently unshared with the account after the experimental run is completed. Figure 3 shows the file's access status through the different experiment phases. The account's password is also updated after each study run so the previous participant will no longer have access.

This sequence allows us to remain fully in control of all the files and data generated during the study, and drastically reduces the possibility of accidental or intentional attempts to alter or delete any experimental files by a participant. Giving participants access to personalize the account settings prior to the study also allow them to work more efficiently during the study, better replicating their typical usage of the software.

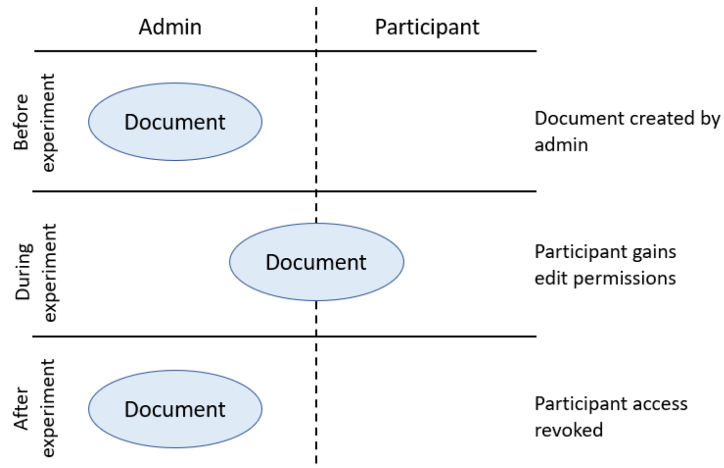


Figure 3 Experiment Document Access Management

Onshape's file structure behaves differently from most typical CAD programs. Essentially the documents act as "containers", capable of storing a collection of files including parts, assemblies, and even pdf documents or images, displayed as tabs within the document, similar to tabs in modern web browsers. We took advantage of this flexibility and uploaded all the instructional drawings as pdfs to each participant's experiment document. Each document contained one Part Studio (Onshape's name for a solid part modelling environment) and five pdf tabs. Figure 4 is a screen capture of the Onshape modelling interface, and the arrow points to the pdf tab for the Step 1 drawing.

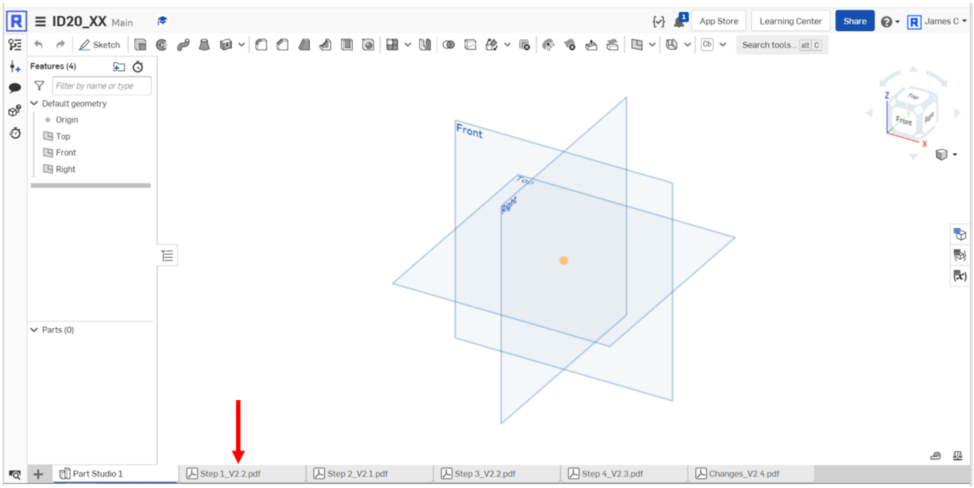


Figure 4 Illustration of Onshape Document Interface (Arrow Points to the First Drawing Tab)

3.8.3 Task 1

The first experimental task involves the participant creating the model shown in Figure 5 below. The names of the major features are labeled to facilitate referencing individual features in the rest of this document.

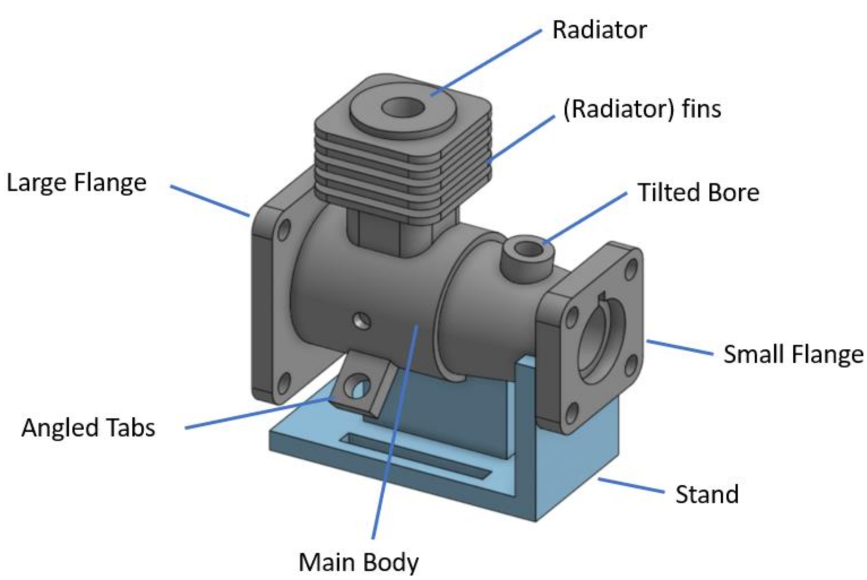


Figure 5 Experimental Task Model with Major Feature Labeled

It was decided that the modelling task would be split into multiple steps, with each successive step adding additional features to the model until the final model shown above is completed. The progression is shown in Figure 6.

Step 1 establishes the main body feature and the flanges. Step 2 adds the radiator feature. Next in Step 3, the tilted bore, angled tabs, and two small holes are added. Finally, Step 4 involves creating a supporting stand as a separate body.

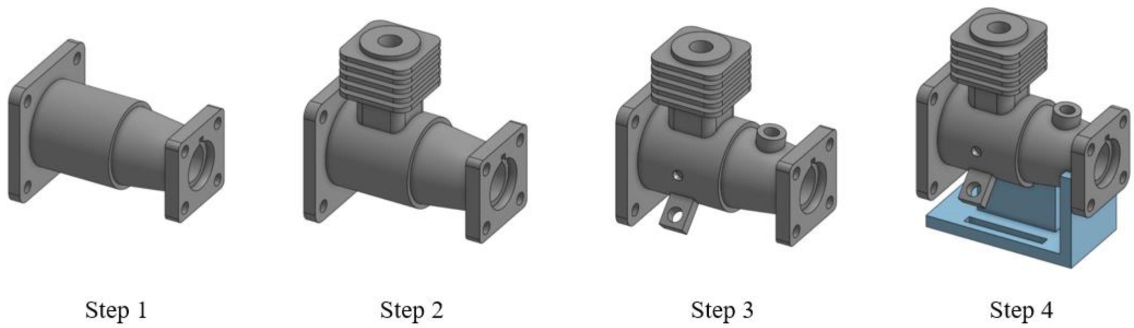


Figure 6 Task 1 Model Progression

Detailed engineering drawings were provided for each step and served as the main sources of information for the participants during the experimental tasks. The drawings included redundant dimensions to allow participants to choose their preferred modelling approach. For example, in Figure 7 we can see that the 142mm, 130mm, and 62.28mm dimensions are technically redundant as they could be all inferred by using other dimensions. Participants had the option to create the angled cylinder in the middle of the part by defining the diameters at both ends (50mm & 62.28mm), or instead defining it with the 50mm diameter along with a 7-degree draft on the outer surface. This fact was made clear to each participant to avoid causing potential confusion.

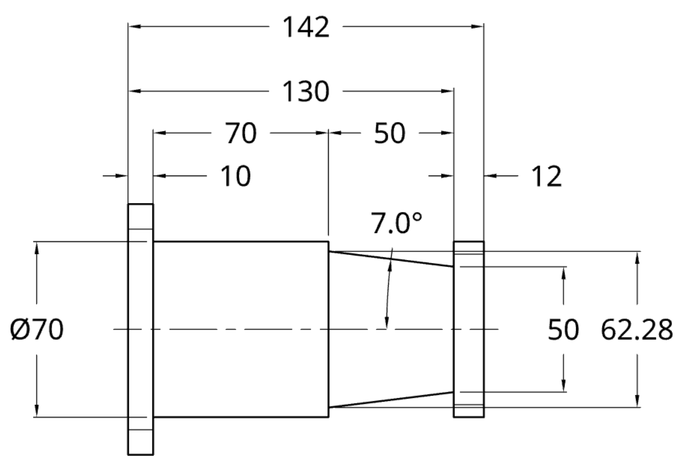


Figure 7 Example Illustration of Drawing with Redundant Dimensions

Dividing the modelling task into multiple steps provides a few benefits:

1. Improves our ability to compare participants' progress. The steps serve essentially as mini checkpoints and allows for comparison even when participants do not complete the full model. This helps to achieve our goal for easily scoring and comparing participants.
2. Replicates a real-life scenario where new features are added to an existing model in a progressive manner. Participants were shown the final model during the introduction presentation, akin to how a real-world design task may start with a conceptual sketch of what the assumed final shape of the product would look like.
3. Having multiple steps allow each drawing to be simpler and easier to parse. This makes the task less focused on testing the participant's engineering drawing comprehension and more focused on the modelling aspect.
4. Increasing the modelling difficulty between each step improves the usability of the experimental task for a wide range of participants, addressing the first of our design goals. Most participants should be able to successfully complete the first step, with increasingly experienced participants able to complete more successive steps.

However, there are also some downsides to this approach:

1. Providing detailed engineering drawings does not fully replicate a real-world modelling workflow where users typically start from a more open-ended problem definition and working towards building a CAD model through several exploration steps.
2. Splitting up the engineering drawings makes planning ahead during modelling more challenging, as participants only see a part of the final model at a time. It should be noted however, that participants were explicitly told they were allowed to look at all the drawings in any order they wished.
3. The participant's ability to read engineering drawings remains a confounding factor that we are unable to isolate/remove. Those who are not used to reading engineering drawings or are used to drawings that follow a specific format (potentially the case for specialized disciplines or fields) may be disadvantaged and perform worse.
4. Although the tasks in each step are designed to be as independent as possible, modeling errors can still cascade between steps, causing potential errors or feature failures from an earlier step to negatively impact performance on the later steps.

Next, we will discuss some of the design considerations behind the modelling task to achieve the experimental design goals discussed earlier, namely maintaining a large solution space, providing opportunity to utilize efficient modelling strategies, and minimizing trivial and time-consuming tasks as laid out in our objectives. The full drawings for each step are available Appendix B.

3.8.3.1 Step 1

The model in Step 1 (Figure 8) can be broken down into three major components. A cylindrical portion connected to two flanges on either end.

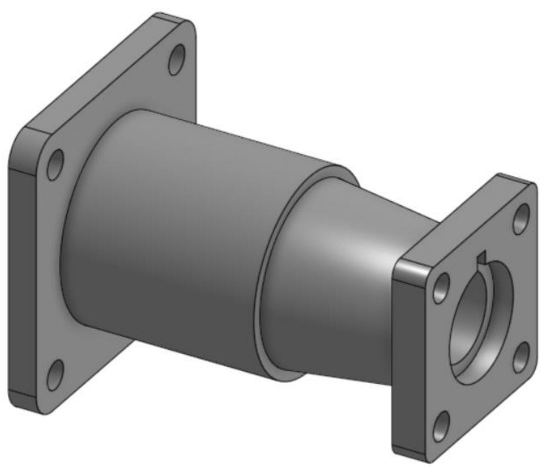


Figure 8 Step 1 Model

The flanges are both square in shape, along with through holes that resemble conventional mounting holes. The profiles were chosen to be square to see whether participants would choose to dimension both sides or utilize the equal constraint, as shown in Figure 9.

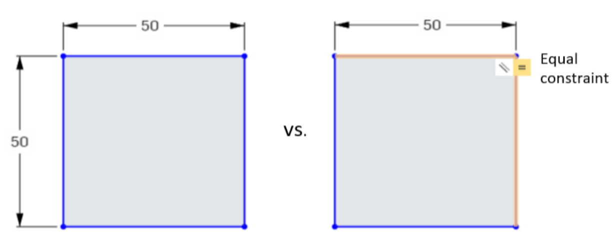


Figure 9 Two Methods for Dimensioning a Square

While there is no correct answer, we were curious to see how participants infer the design intent and decide what dimensioning scheme would be most appropriate for features like these.

The middle cylindrical portion includes two subsections, a larger and a smaller cylinder with a distinct step between them (Figure 10).

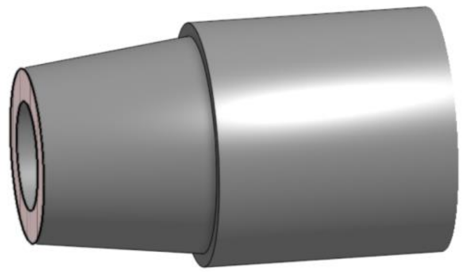


Figure 10 Middle Portion for Step 1's Model

A tapered central bore that cut through the entire part was also present. The taper of the smaller cylinder and central bore was added to expand the number of potential model approaches. Even though this is a fairly simple geometry, multiple solutions were still available. A few include:

1. Two cylindrical extrudes + drafted outer surface + drafted extrude-cut for the center bore
2. One single revolve feature to accomplish all features (including central bore)
3. Lofted feature to create smaller cylindrical section + lofted feature for central bore

Figure 11 shows how the smaller flange complexity was increased by adding a recessed section with a keyway:

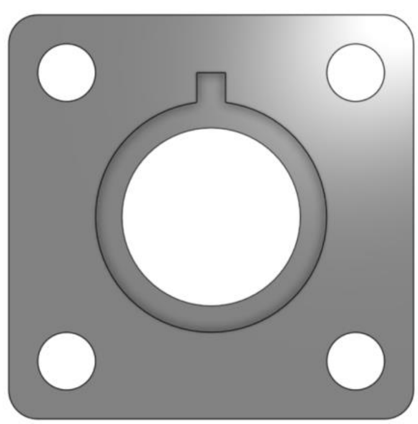


Figure 11 Small Flange Recessed Portion with Keyway

A cross sectional view shown in Figure 12 demonstrates how the various features combine to create a moderately complex overall geometry and highlights the importance of proper feature order management as well as feature definitions.

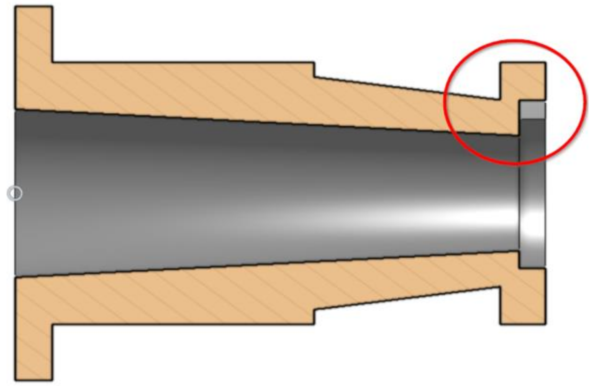


Figure 12 Cross-sectional View of Step 1 (The Circled Region Requires Extra Care)

3.8.3.2 Step 2

In Step 2, the radiator feature is added to the model from Step 1, as shown in Figure 13.

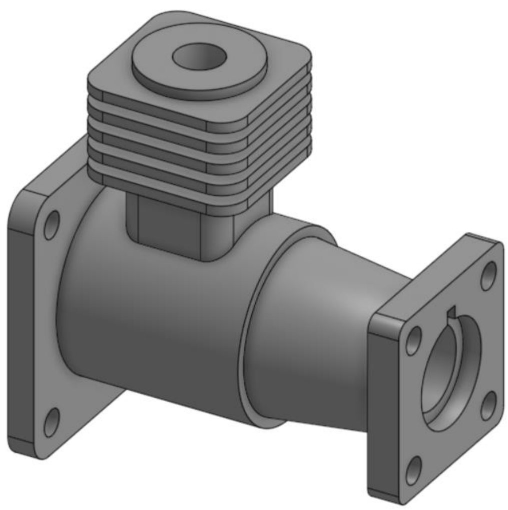


Figure 13 Step 2 Model

The multiple fins were added to test whether the participants would seize the opportunity to utilize a patterning feature.

At the top of the radiator, in Figure 14, the round extrusion has a different cross-sectional shape compared to what is below the top fin (round vs. square). This was designed to study how different participants set up their models to handle this requirement and how their decisions affect the way their models respond to design changes in Step 2.

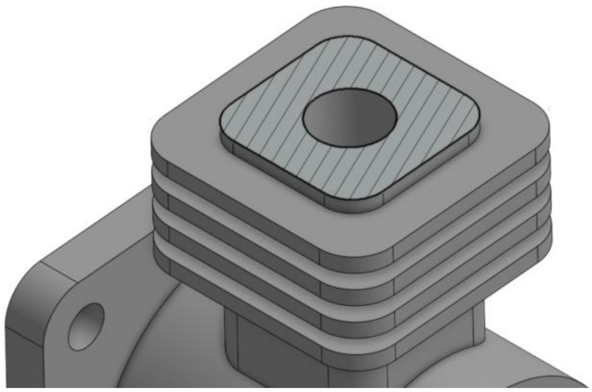


Figure 14 Cross-sectional Shape Below Top Fin (Shaded Section Shows the Square Profile of The Radiator Center)

Note that in Figure 15, the shaft at the center of the radiator also joins with the central bore in the main body. It was expected that poor modelling techniques would likely lead to this feature being missing or requiring extra time and adding additional features to achieve.

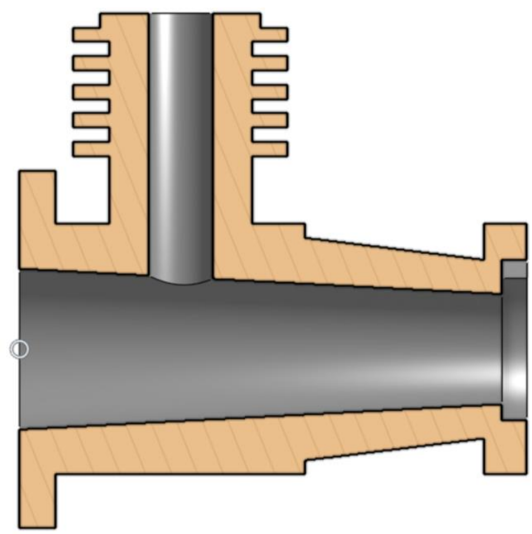


Figure 15 Cross-sectional View of Step 2 Model

3.8.3.3 Step 3

Three separate features are added in Step 3, a pair of angled tabs, two holes on the outer surface of the large cylinder, and a tilted bore extending from the drafted cylindrical face of the main body. Figure 16 illustrates the completed Step 3 model.

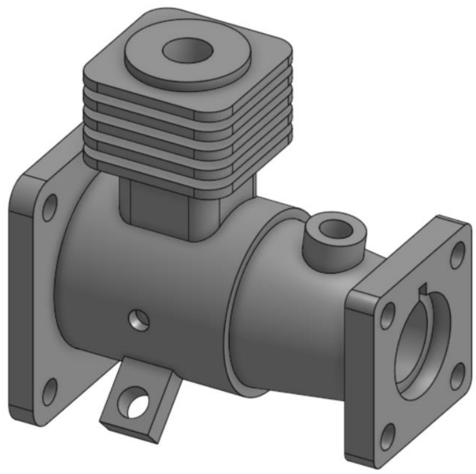


Figure 16 Step 3 Model

The angled tab introduced complexity since the participants would have to determine a way to define their features on an angled reference plane.

The depth of the hole feature was defined from the edge of the outer edge of the cylinder on the drawing, increasing the difficulty and required the use of additional datum features to properly control.

As shown in the cross section view in Figure 17, both the hole and the angled tabs were mirrored about the central plane. We expected most participants to correctly utilize the “mirror” feature to easily create the same feature on the other side of the part.

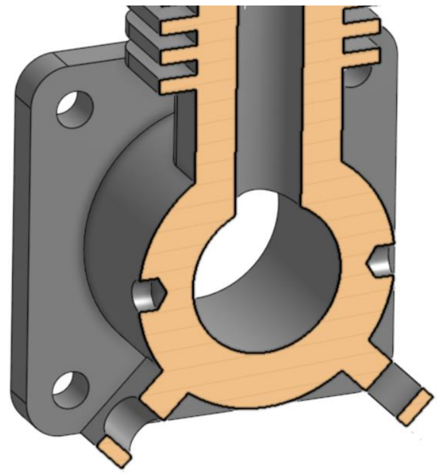


Figure 17 Tapped Holes on the Side (Not Through Holes)

Lastly, the tilted bore was designed to be the most challenging feature to accomplish. It is defined to be perpendicular from the outer surface of the cylindrical face and a specific distance away from the flange. There are many ways to properly capture the geometrical constraints for this feature, and it was designed to serve as a challenge for the more experienced participants. Participants also have to pay close attention to make sure the hole in the center cuts all the way through. Figure 18 shows a cross-sectional view through the tilted bore feature.

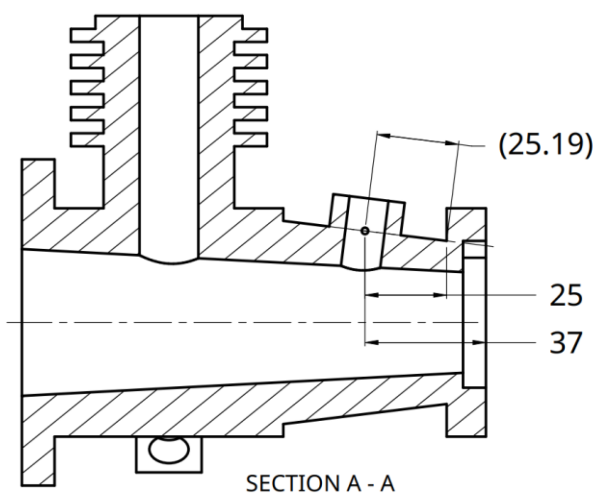


Figure 18 Geometrical Details of the Tilted Bore

3.8.3.4 Step 4

Step 4 requires participants to model a stand that supports the part made in the previous three steps as a separate body, testing the participants' familiarity with multi-body modelling.

The geometry is relatively straightforward; the only difficulty comes from making sure the stand interfaces and matches the contour of the other body properly, highlighted below in orange in Figure 19. In the experiment instructions, participants are asked explicitly to let the geometry of the stand be driven by the main body instead of defining the stand's geometry separately. It was assumed that users unfamiliar with creating driven geometries or multi-body modelling may struggle with this task.

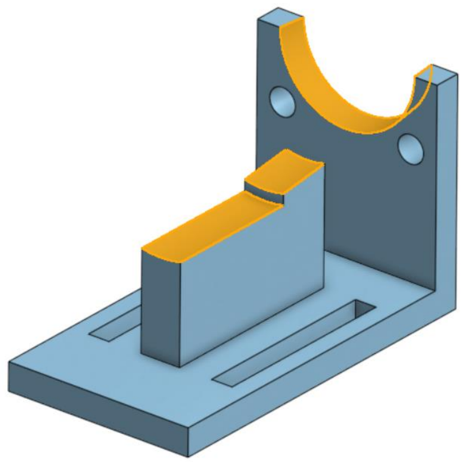


Figure 19 Step 4 Model, the Supporting Stand

3.8.4 Task 2

The time allotted for Task 2 was much shorter, 15 minutes in total versus the 35 of the first task, as most of the changes were not expected to be time consuming. Participants were instructed not to create any additional features, unless they were needed to complete a change. Essentially, participants were asked not to revert to activities carried out in the previous task. Task 2 concluded once the participant finishes all the possible alterations they could complete or when the time is up.

The drawings were split into four separate steps as well, matching the four steps from Task 1. Participants only needed to work up to the step they reached in the previous task. Figure 20 is an example of the change requirements drawing for Step 1. Each drawing included a "summary of changes", an isometric view of the modified model for reference, and dimensions that have been modified. All unchanged dimensions were excluded to reduce clutter.

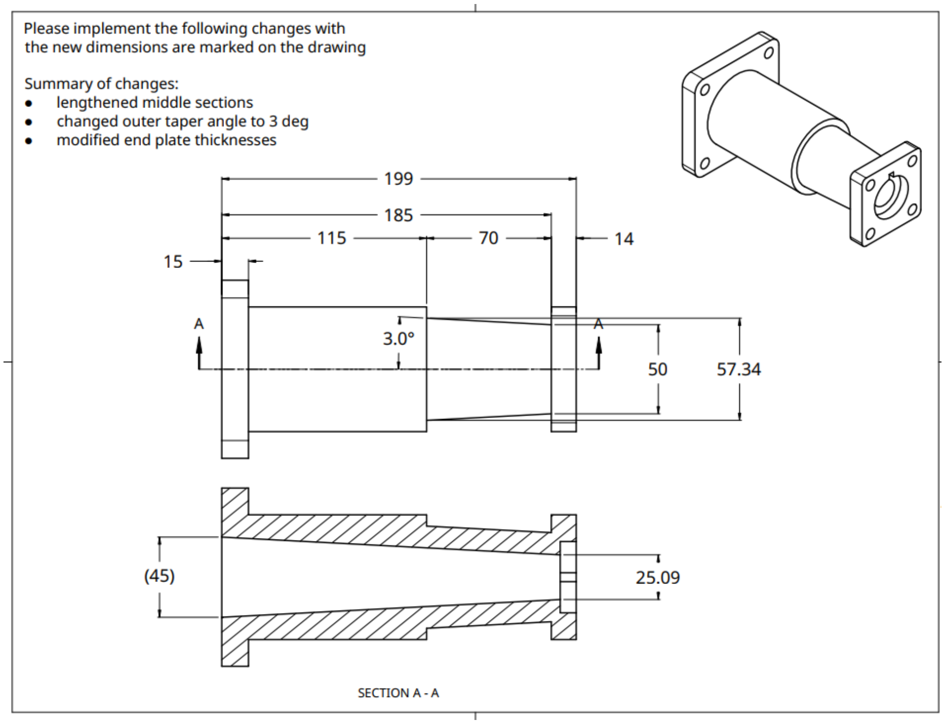


Figure 20 Task 2 Step 1 Drawing

The changes were designed to highlight inefficiencies in a participant's initial modelling approach and ideally catch non-ideal dimensioning schemes or sub-optimal geometrical references that may have been adopted earlier. The changes in Figure 20 were expected to be easily accomplished for those who created a model that is adaptable and well-organized.

An example of a set of more complex modifications is the series of changes for the radiator shown in Figure 21, involving changing multiple geometries, some from circular to rectangular, as well as moving the physical location of the radiator assembly. Since many features in the radiator could be defined to be interrelated, this was expected to be a good measure of how robust or flexible the participant's initial modelling approach is.

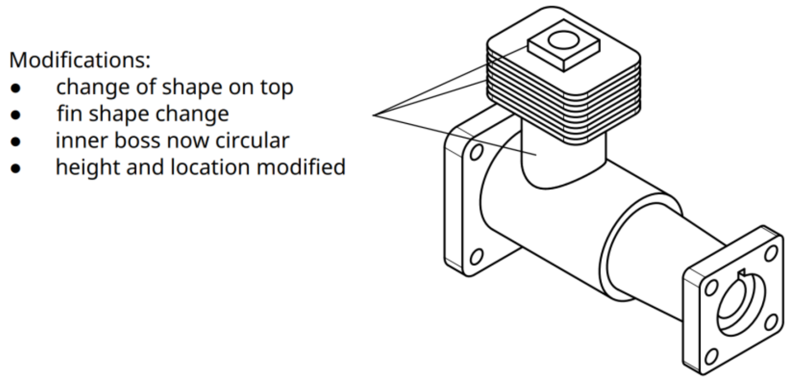


Figure 21 Series of Modifications Designed to Uncover Model Weaknesses

Another task designed to highlight robust and efficient modelling is changing the angles of the tabs as shown in Figure 22. Depending on how the feature was initially created, this modification could be as easy as changing one parameter or require multiple steps to complete if done inefficiently.

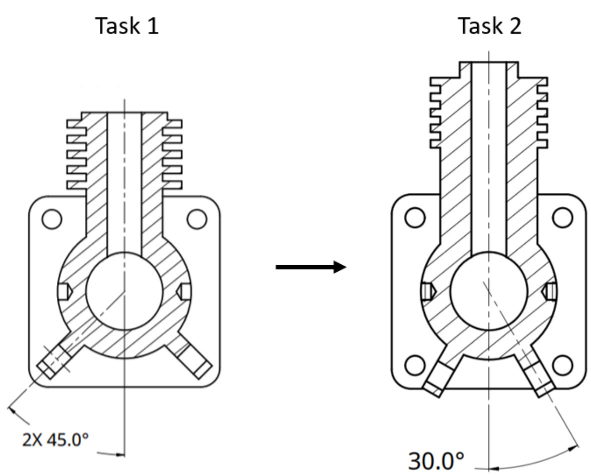


Figure 22 Change in Angle for Tab Feature in Task 2

3.8.5 Interview

After each task, short interviews were conducted. They allowed us the opportunity to ask a variety of questions and gain a better understanding of the participant's modelling strategy, such as how they decided to define and dimension various features, or what datum scheme they chose to implement. Participants were also asked to share any challenges they faced during the study.

After the second task, participants were asked to identify the features or decisions that helped make editing their model easier, as well as what improvements they would make if they were given the opportunity to redo the initial modelling task. The goal was to understand whether a prescribed editing task could promote critical analysis of one's own model and help participants identify weaknesses in their initial approach.

3.9 Efforts to Maintain Experimental Consistency Between Participants

Since the study was fully virtual, we attempted to make the experiment as consistent as possible between participants through the following measures:

1. Participants were instructed to put their phones away or on silent and mute notifications from messaging programs such as Slack or Microsoft Teams if possible, to ensure they could remain focused and undisturbed throughout the duration of the study.
2. Participants who used multiple monitors were requested switch to using only one screen for the study, reducing the environmental variables. Unfortunately, not all the participants had the same screen resolution or screen size, a factor out of our control.
3. All experiments were conducted over Zoom and all CAD modelling performed on Onshape.
4. The same written instructions and drawings were provided to each participant.
5. A script was developed for the presentation, so each participant was shown the same slides and provided the same set of verbal instructions.
6. Timers were setup for each portion of the experiment to make sure each participant had the same amount of time to work on the tasks.

4 Demographics Summary

In total, 90 individuals expressed interest in participating in the study. After filtering out individuals who did not meet our requirements, 40 were invited to participate in the study. Of the 40 invited, 19 participated in the study.

The participant pool gender ratio was heavily skewed towards men, with only 2 of the 19 experiment participants identifying as female. This is acknowledged as sub-optimal but was difficult to remedy given the lack of control over the audience of our recruitment messages.

Unlike many other university research studies, more than half of our participant pool (11 out of 19) was currently employed full time in industry. Nine of the 11 stated they perform engineering design as part of their regular work. The types of work performed ranged from detailed part level design to assembly design to design for manufacturing. Four had obtained bachelor's degrees, three had master's degrees, and the last three ranged between high school and associates degrees. The average age of this group was 35 years old, with a range of 21 and 65.

The remaining 8 participants were all students. Two were about to begin their undergraduate degrees, while the rest were either first or second-year undergraduate students. All the students were in the sciences field of study, with 5 of them currently enrolled in mechanical engineering. It is also interesting to note that 6 out of the 8 students were working in the industry as a co-op or internship students at the time of the study. Their average age was 18.9, with a range of 17-20.

All but one participant were located in North or Central America, and the majority of them identified as Caucasian, except for 4 individuals each identifying as Arabic, Latin American, Asian, and Indigenous.

We asked participants to specify the CAD software solution(s) they were most familiar with from a list of most commonly available commercial CAD programs. All 19 participants selected Onshape as one of their choices, with many participants also selecting SolidWorks, NX, Creo, AutoCAD, and Fusion360 in addition. The complete pre-study survey and initial interest form are available in Appendix C and D.

4.1 CAD Experience

In addition to the question posed in the initial interest form asking participants to self-select their CAD expertise level (novice, intermediate, or expert), We also posed an additional question during the pre-study survey. First, we asked participants to state how much experience they have in CAD across all CAD programs. As a follow up question, we asked participants to state how much of that experience was spent in Onshape specifically. Participants were given the option to either estimate total hours (e.g. 600 hours) or number of years and months (e.g. 4 years, 3 months) for both questions.

Interestingly, given the two options, all participants chose to express their experience in number of years and months instead of total number of hours of CAD usage. This is likely due to the difficulty in estimating and adding up hours of CAD usage over potentially many years.

We separate the participants into two groups, intermediates (n=9) and experts (n=10), to see if there are significant differences between them in terms of CAD experience. Somewhat surprisingly, when looking at overall CAD experience, the median for both the experts and intermediates was 60 months, with similar ranges as well, between 34 to 396 and 8 to 360, respectively. The experts, however, did have a higher mean of 121.7 than the intermediate's 84.2. We chose to compare the medians for both groups given the large spread (see Figure 23).

Looking more specifically at Onshape experience, we can see a clearer distinction between the two groups. The experts have a median of 23.5 months compared to the intermediate's median of 15. The participants who reported extensive overall CAD experience mostly spent the bulk of their modelling hours in one of the established CAD tools.

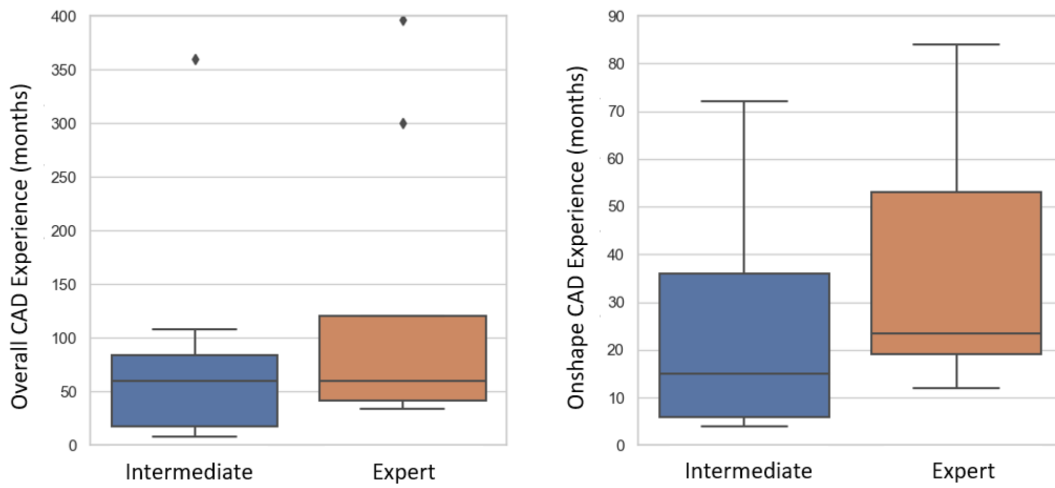


Figure 23 Comparing Overall (left) and Onshape Specific (right) CAD Experience by Self-identified Experience Level

As we will discuss later in more detail, our analyses show that self-reported CAD experience and performance level in this experiment are not well correlated. One reason may be due to the differences in CAD usage frequency between participants. One year of highly intense and consistent modelling for one person may equal to many years of usage for someone else who only periodically uses CAD in a less vigorous manner. Studies have also shown that people often overestimate their competence, as identified by Dunning and Kruger's hallmark study on the difficulty in recognizing one's own abilities (or lack thereof) [32]. More recently, Stone et al. also discovered that people's self-rated CAD proficiency level was generally inaccurate in a team-based design competition study [33]. Yet another reason may be that the experimental task was unable to accurately measure each participant's CAD performance.

In future studies, some form of a CAD proficiency test prior to the experiment will be necessary. Unfortunately, that increases experiment logistical complexity as well as the cost and time required. One thing is for certain, CAD skill determination is a non-trivial challenge worth further analysis and careful consideration in future studies.

5 Participant Model Analysis

5.1 Scoring Criteria

Since the primary goal of the study was not to judge and score the quality of the participants' models, as that expands the scope significantly, we instead opted to focus more on the actions of the participants during modelling in this exploratory study. Nevertheless, developing a standardized method of comparing participants and measuring their relative task completion and performance was still needed.

Creating a set of metrics that can objectively measure how well a CAD model is made is extremely difficult. Therefore it was decided, for simplicity, to reduce the model down to a set of dimensions that fully define the geometry and use them to check each participant's model. Essentially, if a participant's model includes all the correct values within the set of geometry-defining dimensions, then we can assume it is most likely geometrically accurate. For the purposes of this study, we are looking for both completeness and correctness in the participant's model, so someone who completes the full model but makes numerous mistakes should be penalized.

Drawings were created for assessing the participant models. The process was iterative, where any common mistakes in participants' models that we noticed but were not included on the drawings were added so all the other models are checked for the same mistake as well. To maintain consistency, drawings were created for each of the four steps in Task 1 and Task 2. We also included a few extra non-dimensional checks to try and catch any corner cases or other common mistakes that aren't directly defined by a dimension. Figure 24 shows the drawing created for assessing participants' Step 1 models. Each dimension is labeled with its unique name, such as "S1D2", to maintain consistency during the assessment process.

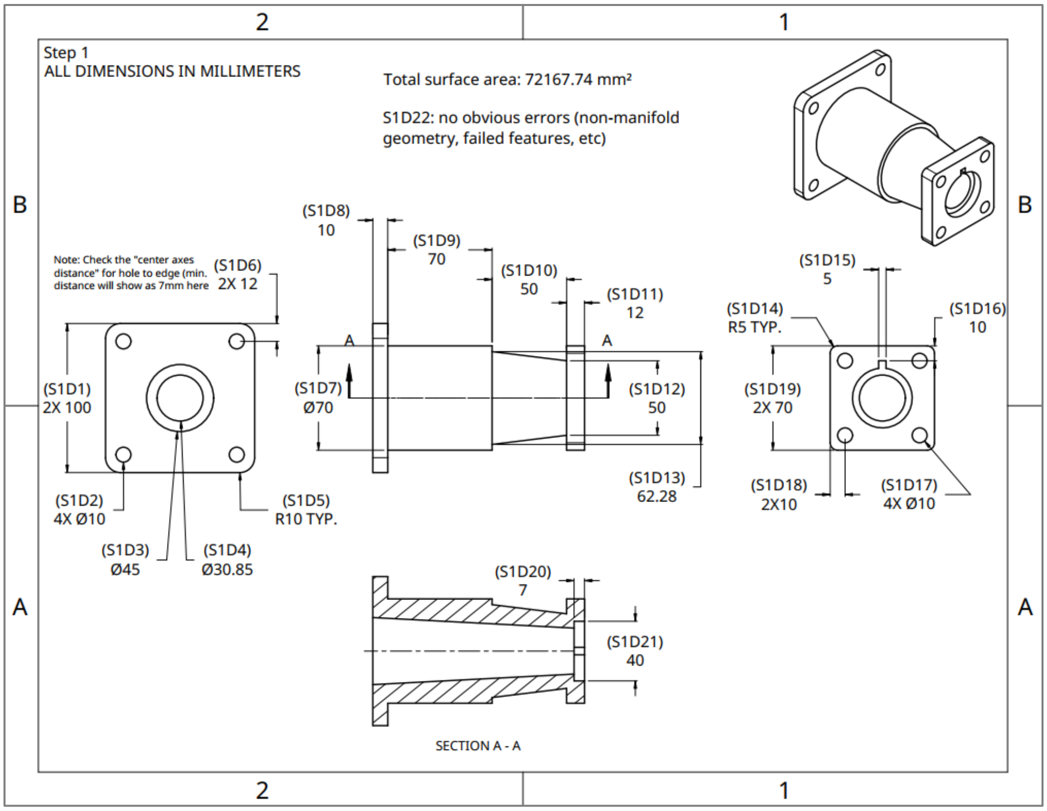


Figure 24 Example of Assessment Guide for Task 1, Step 1

To avoid penalizing the same error twice, we took special care to avoid adding dimensions that could be the combination of two or more other dimensions. For example, in Figure 24, the overall length dimension could be obtained from summing dimensions D8, D9, D10, and D11, and was therefore not included as a dimension to be checked during assessment.

In total, there are a total of 60 dimensions for Task 1 and 20 dimensions for Task 2 to be checked. During assessment, each dimension of a participant's model was checked in CAD and marked as either "present and correct", "present but incorrect", or "did not attempt" on a spreadsheet. This allowed us to calculate two aggregate scores we call "completeness" and "correctness", which we will use in Section 5.2 to compare Expert and Intermediate participants.

The first score, out of 80, represents a participant's overall progress for the entire experiment, accounting for modelling accuracy. It is the number of dimensions marked as "present and correct". A participant who completes both the first and second task but produces a low-quality model with many errors could potentially score lower than someone who makes less progress but is diligent and makes very few mistakes.

The second score, "correctness", is the ratio of the number of "present and correct" dimensions over all attempted dimensions (either "present and correct" or "present and incorrect"). This metric is meant to remove a participant's overall progress from the equation and focus on the participant's ability to accurately create the model according to the drawings. For example, a meticulous participant who only finishes two out of the four steps during the experiment may still be able to score highly for "correctness", even if they did not manage to make as much progress as others.

5.2 Expert vs Intermediate Participants

One of the experiment objectives was to explore what sets apart the higher performing CAD users, so we decided to see whether the self-identified experts performed better than the intermediate participants, then further explored what the differences in their actions were, if any.

We first started by separating the participants into two groups with their self-identified ratings. When ranked by their completeness scores, we found that two intermediate participants ranked in the middle of the group of self-identified experts. On the other hand, two of the experts were found to have performed poorly and scored at about the average of the intermediates, signifying they have not made much progress during the experiment. We re-categorized the first two participants as experts, and the latter two as intermediates.

Looking at the last step each participant managed to complete in Task 1 (see Table 1), we see that as expected, the experts on average were able to cover more ground within the allotted time, suggesting they are more efficient at modelling when compared to the intermediates.

Table 1 Last Completed Step vs Experience Level

	Step 1	**Step 2**	**Step 3**	**Step 4**
Intermediate (n=9)	9	6	0	0
Expert (n=10)	10	10	6	3

We decided to adopt the idea of the creation/revision ratio put forward by Xie et al. to compare the two groups [24], albeit using it to infer a different metric. The design challenge posed to participants in Xie et al.'s study was much more open-ended in nature and included many cycles of design iterations. Their experimental software also captured a different set of actions as ours.

Xie et al. used the creation/revision ratio as an indicator for a participant's reflectiveness during modelling. In our study, the modelling task given to participants was very well defined. The participant's focus was to create a model with the same geometries and dimensions as the ones shown in the drawings. As such, we believe the creation/revision ratio in our study reveals more about how well a participant is able to define a feature correctly in the first pass, and perhaps in extension, how confident the participant is with their modelling ability, rather than how reflective the participant was during the experiment.

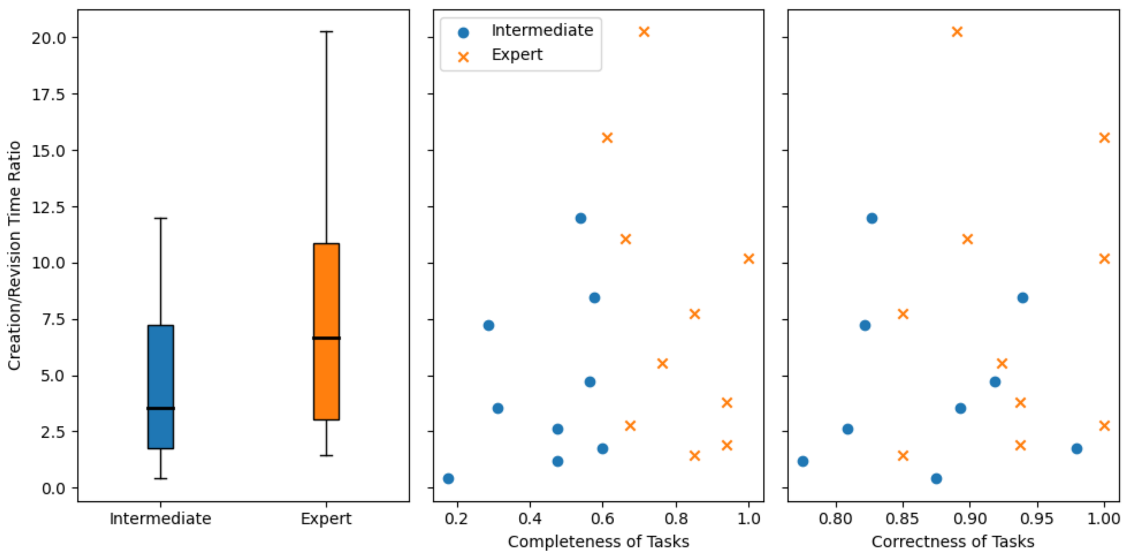


Figure 25 Creation/Revision Time vs Experience Level, Completeness, and Correctness

In the leftmost subplot in Figure 25 we see that experts had, on average, higher creation/revision ratios. This matches with our observations during the study. The experts, having more experience, were generally more able to define features fully and correctly during initial creation. That translates to less of a need to backtrack and edit earlier features.

The next two subplots in Figure 25 shows the completeness and correctness of all the participants plotted against their creation/revision ratios. The datapoints for the intermediates are drawn as circles, while the experts identified by crosses. There appears to be little correlation between either the completeness or correctness and the creation/revision ratio. This suggests that this ratio may not necessarily be a good metric for estimating a particular person's CAD performance.

Another interesting finding is that the correctness scores between the two groups overlapped significantly when we look at the positions of data points along the x-axis in the rightmost subplot.

We see that while some experts were able to complete more work, they have sacrificed some accuracy and model quality. On the other hand, some intermediate participants instead opted for the “slow and steady” approach, where they scored lower on the completeness metric, but made very few mistakes for the features they did attempt to model.

5.3 Modelling Efficiency

Existing literature suggests that more experienced CAD users should be able to complete the same modelling task while using fewer features in when compared to those with less experience [28]. Note that we use the word “feature” here to refer to CAD modelling functions, such as extrude, revolve, chamfer, etc., and not to refer to physical geometries of the object that is being modelled. This is based on a few understandings regarding CAD modelling. First, CAD modelling is highly dependent on feature order, a poorly thought-out approach will often require users to add additional features to fulfill the original modelling intent. Second, experienced users are more likely to notice opportunities to reduce the number of CAD features required by utilizing techniques such as creating master sketches, leveraging automatic feature referencing, or driving key parameters with custom variables. This effect is likely to amplify as the model intricacy increases and complex feature interdependencies begin to form. As Hamade et al. have discovered while studying new CAD users’ learning process, the number of features is highly correlated to modelling time and that students reduced their feature-count throughout their learning process for models of a similar complexity level [8].

To see if our intermediate and expert participants also exhibit a difference in this manner, we tabulated the features each participant used to complete each of the steps in Task 1 and compared the group means (see Table 2). The difference between the two groups in our study was not found to be statistically significant.

Table 2 Tabulation of Number of Features Used to Complete up to Each Step in Task 1

	Avg. features required for Task 1 Step 1	**Avg. features required for Task 1 Step 2**	**Avg. features required for Task 1 Step 3**	**Avg. features required for Task 1 Step 4**
Intermediates	15.2 (n = 9)	26.5 (n = 6)	-	-
Experts	14.7 (n = 10)	25.1 (n = 10)	38 (n = 6)	47 (n = 3)
t-test	$t(17) = 0.26$, $p = .397$	$t(14) = 0.47$, $p = .323$	-	-

There are a few potential reasons why we observed such small differences between the two groups. The modelling task given during the study was not highly complex, which limits the usefulness of adopting the more complex modelling techniques, such as creating master sketches to drive multiple features. Interview findings presented in Section 6.4 confirms this proposition. These approaches often require a larger upfront investment in terms of time and energy, with the expectation of improved efficiency at a later stage. In fact, one participant specifically stated that if the modelling task was more difficult, he would have switched his approach to using a master sketch.

A few participants also expressed feeling the need to complete the modelling tasks as quickly as possible, since they knew there was a limited amount of time available. Even though during the initial presentation all participants were asked multiple times to not rush, many seemed unable to resist the urge. We suspect that these participants resorted to using a more primitive modelling strategy in a bid to save time, which likely also translates to a higher feature count.

Properly capturing design intent while preserving model flexibility and maximizing model efficiency is a complex balancing act, with the calculus changing greatly depending on the particular model being created. Through this study we discovered that the matter of analyzing a participant’s modelling efficiency involves much more than counting the number of features used within a specific modelling task. Future studies could explore the possibility of assigning different weights for each feature type to arrive at a weighted sum instead of a simple feature count, since features such as lofts or sweeps tend to be more complex than simple fillets or extrudes.

6 Findings from Participant Interviews - Modelling Strategies and Techniques

Two short interviews were conducted for each experiment, one after the first experimental task, the other after the second experimental task. A series of questions were prepared to help guide the interviews, and additional impromptu questions were added to obtain better clarity or further inquire about noteworthy observations made during the experiment. The interviews were designed to develop an understanding of the participant's strategy adopted during the study. We also inquired about each participant's general CAD strategies and preferences, not specific to the task given during the experiment.

The set of questions posed to the participants after the second task explored the aspects of the participant's model that helped improve its modifiability, as well as the participant's thoughts on what they would have liked to do if given the opportunity to redo the entire experimental task from the start. The goal was to work with the participant through a reflective exercise and determine whether being asked to make a series of changes to one's own model presents a good learning opportunity when it comes to CAD training.

We summarized a few major recurring themes and interesting findings after analyzing the interview notes and transcripts.

The list of questions is available in Appendix E.

6.1 Reference Principal Planes and the Origin When Possible

Several expert participants discussed their strategy of using the principal planes and the origin as references as much as possible to improve model robustness. Participant 11 stated that *"the most stable references will always be the origin and the three principal planes. Anytime you add something on top of that, you are basically adding another degree of separation from those geometries, which adds to the complexity".* Few intermediate participants considered this as a strategy, which is in line with Peng et al.'s finding of novice CAD users generally having a weak understanding of utilizing the principal planes while modelling [34].

Since the origin and the three principal planes are foundational features of the geometrical/coordinate system for each CAD document, referencing dimensions and other geometrical entities to these immovable features is sound advice.

It is interesting to note that while there is little debate on the usefulness of referencing the principal planes in feature definitions, the practice of creating additional datum planes is less agreed upon. Participant 6 discussed adding multiple datum planes during modelling to serve as references for end conditions and act as sketch planes for different features. Participant 9, on the contrary, explicitly stated his preference of not adding any additional planes during modelling. A more complex modelling task is likely needed to properly test the different strategies before we can determine whether one approach is generally more advisable.

6.2 Additive vs Subtractive Modelling

Observing the participants' modelling actions, we noticed two different styles of modelling approaches: additive and subtractive modelling. Participants 11 and 9 both expressed their approach as being subtractive, where they begin by considering the largest bulk solid and progressively add features in CAD that remove material from it. This modelling approach mirrors common manufacturing operations, such as milling and turning, and helps the designer consider manufacturability during modelling. Participant 11 explained his affinity to this approach with his background in machining.

On the other hand, CAD designers following the additive modelling approach instead opt to add material at each step until the final desired geometry has been fully created. This approach may be more intuitive to new CAD designers without extensive background in traditional manufacturing techniques since the user simply adds individual features to the bulk one by one.

From this experiment, we discovered that a person's background and previous experiences can have a significant impact on their preferred modelling approach. With additive manufacturing technologies such as 3D printing gaining widespread adoption in all stages of the engineering design process, it would be interesting to study the strategies adopted and developed by younger CAD designers who are less restrained by some of the limitations with traditional manufacturing processes.

6.3 Being Adaptable

Another key takeaway from the experiment is the idea of being adaptable and flexible when modelling. Seasoned CAD designers remind themselves to keep their minds open to different approaches as they model and are not afraid to make big changes if they realize there is a better solution available. Some people, such as Participant 11, even practice remaking entire models from scratch after the first iteration as an opportunity to explore new solutions and try alternative approaches. While time intensive, this is undeniably a good way for a new CAD user to fully explore the solution space and practice adopting different perspectives.

6.4 Utilizing Master or Layout Sketches

Four expert participants discussed the general strategy of using master sketches to outline the overall part structure and serve as a blueprint for the model to drive all the major features. This approach helps manage feature dependencies and improves model robustness significantly and has been extensively studied in literature [35].

The consensus was that while the approach is powerful for model feature dependency management and improving model robustness, the expected benefits did not outweigh the time and effort requirement during the experiment.

7 CAD User Actions Analysis

7.1 Introduction to Audit Trails

Onshape's documentation states that Audit Trails "display every event on a specific document or for a specific user for a specific timeframe" [36]. For the purposes of this study, we will simply treat them as data-logs of actions taken within each specific document. At a high level, Audit Trails record the following:

- **Event time** - The date and time the event occurred.
- **Document name** - The name of the document.
- **Element** - The Onshape tab in the document: Part Studio, Assembly, etc.
- **User**- The name of the user involved in the event.
- **Description** - A description of the event.

The event time for each Audit Trail entry is recorded in Universal Time. Events are recorded down to a resolution of a second, which is sufficient for our purposes. The timestamps also aid in finding corresponding sections in our video footage. In future multimodal studies where synchronization is important, the event time could be useful in aligning the Audit Trail with other data sources.

In the following sections we start with explaining some benefits of using Audit Trails, then discuss in further detail the Audit Trail structure as well as its limitations. We detail how to extract useful data from the raw Audit Trails, then discuss the insights gained from analyzing our participants' data.

7.2 Benefits of Using Audit Trails

Traditionally, datalogging in design experiments is done using custom scripts at the local level, on the same computer that the CAD software is running on. This diversion of computational power increases the resources necessary to prevent any slowdowns within the CAD software during an experiment. This effect is compounded if multiple streams of data need to be recorded, such as a combination of screen recording, webcam recording, and keyboard + mouse cursor tracking, necessitating expensive computer hardware to be purchased or complex multi-computer setups designed to spread the workload [37].

One benefit to our experimental protocol is that all the datalogging is handled by the Onshape's backend servers, meaning there is no performance penalty or additional setup requirements. Onshape's servers also handle the majority of the CAD computational workload such as model regeneration and boundary representation calculations, leaving the end user's computer a straightforward task of simply displaying a rendered 3D representation of the current CAD model. This lowers the hardware requirements significantly for all the participants in virtual studies, but also for research labs when conducting in-person experiments.

Our experiment protocol also takes advantage of the video footage being recorded onto the cloud in real time, making the entire process much more resilient to potential disruptions, such as internet connection issues, without risking losing experimental data.

As we will demonstrate in later sections, analyzing and categorizing the actions of a CAD user can be done through an automated process that is highly efficient. Compared to manually coding a user's actions, as has been done in various studies [38][39][40], our methodology significantly reduces the time and effort required to analyze a CAD user's actions during a design study.

Since each Audit Trail entry corresponds to a particular user, we could conceivably extend this study framework and methodology to team-based activities in the future while retaining the ability to easily isolate individual actions from the collective. Simultaneously analyzing the team's actions as well as one specific team member's actions could be easily accomplished.

7.3 Process to Obtain Audit Trails

The process to obtain Audit Trails is straightforward. Using the filters on the Onshape website, we specify the document we are interested in and then filter by user. In this case we search for the entries associated with the experiment Onshape account we have created.

Figure 26 is a screen capture of the Onshape interface for reference:

Audit Trail

▸ Filters Date is in the past 5 weeks Document is "Audit trail testing" Project is any value Feature is any value Event is any value User is Guest is any value User Email is any va

	Event Time	Document	Tab	User	Description
150	2021-08-05 05:27:43	Audit trail testing	N/A	James C	Close document
151	2021-08-05 05:27:43	Audit trail testing	Part Studio 1 Copy 1	James C	Tab Part Studio 1 Copy 1 of type PARTSTUDIO closed by James C
152	2021-08-05 05:27:39	Audit trail testing	Part Studio 1 Copy 1	James C	Edit : Extrude 2
153	2021-08-05 05:27:39	Audit trail testing	Part Studio 1 Copy 1	James C	Commit add or edit of part studio feature
154	2021-08-05 05:27:29	Audit trail testing	Part Studio 1 Copy 1	James C	Start edit of part studio feature
155	2021-08-05 05:27:26	Audit trail testing	Part Studio 1 Copy 1	James C	Commit add or edit of part studio feature
156	2021-08-05 05:27:26	Audit trail testing	Part Studio 1 Copy 1	James C	Edit : Sketch 2
157	2021-08-05 05:27:26	Audit trail testing	Part Studio 1 Copy 1	James C	Add or modify a sketch
158	2021-08-05 05:27:19	Audit trail testing	Part Studio 1 Copy 1	James C	Start edit of part studio feature

Figure 26 Screen Capture of Audit Trail Details on Onshape.com

After the parameters are set, the Audit Trail can be exported from Onshape as a .csv or .xlsx file. We can then perform any necessary data cleaning before performing analysis.

During the study, participants were asked to open the experiment document right before each experimental task and asked to close the document once the task was over, clearly delineating two chunks of data in the Audit Trail for the two experimental tasks and marking when they start and end.

The downloaded Audit Trails for each participant are processed and split into two separate Audit Trail files labeled “Task 1” and “Task 2”, each starting with the “Open document” entry and ending with “Close document” entry. Depending on the circumstances, irrelevant Audit Trail entries before and after the experimental portion will be removed.

If, during the study, time passes while the document was open without participant having started yet or the document was kept open after the study has ended, the event times are manually adjusted during processing to better reflect reality with the help of the video recordings. Such circumstances could happen when participants prematurely open the experiment document before being instructed to do so or forgetting to close the document after the task has finished.

On average, we collected 375 data points for each participant for the first experimental task (35 minutes), and 159 for the second experimental task (15 minutes). Full details on the number of datapoints captured is summarized in Table 3.

Table 3 Summary of Audit Trail Datapoints

	Mean	S.D.	Min	Max
Audit trail entries per participant (Task 1)	375	135	157	677
Audit trail entries per participant (Task 2)	159	62	53	314

7.4 Audit Trail Structure and Analysis

Documentation on the Onshape Audit Trail is not available, so we had to uncover the Audit Trail structure through extensive experimentation.

By parsing through Audit Trail entries sequentially and analyzing each entry's description text, we can extract and infer the user's action. We categorize the actions the Audit Trail captures into two groups. The first group of actions is demarcated by one or more entries for the start and for the end. For example, when a user adds a new extrude feature, two Audit Trail entries whose descriptions are "Add part studio feature" and "Insert feature : Extrude 1" will be added to the Audit Trail, as illustrated in Figure 27. Depending on the circumstances, other Audit Trail entries may exist between the two entries.

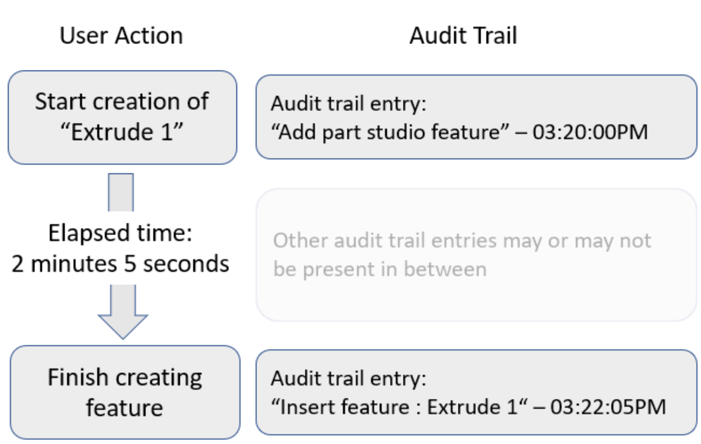


Figure 27 Example Audit Trail Entries for a New Extrude Feature

By calculating the time difference between the two Audit Trail event times, we can calculate exactly how long it took the user to create the "Extrude 1" feature. By the description text, we can also infer what type of action was performed, as well as what the relevant feature was for each action.

During the Audit Trail analysis, we sum up the total time spent in each of the seven Group 1 actions, which includes the amount of time spent reading drawings, creating sketches, creating features, editing sketches, and editing features. We also keep track of how much time was spent on creating or editing features that were eventually cancelled by the user before committing the feature. We use the sum of the feature creation time and feature edition times to calculate the "creation revision ratio" reported in Section 5.2.

The second group of actions show up in the Audit Trail as single instances, without corresponding start or end times. An example is when a user deletes a sketch or suppresses a feature. Given the nature of these actions, they result in only one Audit Trail entry each; therefore, we are unable to calculate the duration of these actions.

Table 4 details the actions categorized under each group.

Table 4 Audit Trail Actions Categorized into Group 1 & 2

Group 1. Actions with derivable time durations	**Group 2. Actions without time durations (single instances)**
Open & close a drawing	Delete a sketch/part studio feature
Add a new sketch	Suppress a feature
Add a new part studio feature	Rename a sketch/part studio feature
Edit a (existing) sketch	Show/Hide a sketch/feature
Edit a (existing) part studio feature	Move Feature/Rollback Bar
Cancel editing a sketch/feature	Suppress/ Unsuppress feature(s)
	Create Folder

To maintain consistency with the terminology used by Onshape, we use the term "Part studio feature" to encompass all 3D modelling features, such as extrude, revolve, fillets, patterns, etc. Sketches are considered features as well but have additional Audit Trail entries associated with them given their unique nature compared to other features.

A complete mapping of CAD actions and their associated Audit Trail descriptions is available in Appendix F.

While the Audit Trails allow us to capture a wide array of actions, we must also discuss their limitations. Actions taken during feature creation are not recorded, such as when a user is defining the depth of an extrusion, or the angle of a revolve feature, as illustrated in Figure 28. From the Audit Trail we are only able to discern when the user started creating or editing a specific feature and when that feature is committed (completed).

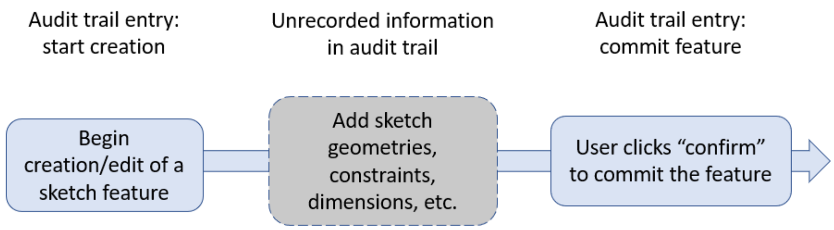


Figure 28 Representation of Audit Trail Data Capture Coverage

The biggest handicap to this limitation emerges when analyzing sketch features. Since we are unable to track the actions taken during sketching, a participant who spends a significant amount of time during the experiment actively sketching would generate very few Audit Trail entries.

Sketch creation can often be difficult for novice CAD users who are unable to construct well-defined sketch entities properly and efficiently. As such, they will often spend a significant amount of time within each sketch before they click "confirm". This renders the usage of Audit Trails for design research impractical if the primary actions are creating and editing sketch features, or if the anticipated participants are unfamiliar with using CAD.

7.5 Python Code Structure

Given the likelihood of future Onshape CAD studies being carried out by the research lab, the intention was to develop the codebase to be easily useable by anyone in the future. The code for analyzing the Audit Trails was written in Python and designed to be a "one-click" solution where it will accept an Audit Trail and automatically perform all necessary and relevant analyses.

The code includes separate modules. First the raw Audit Trail is read in and checked for its completeness. Any inconsistencies will be flagged to the user. If all the inconsistencies are resolved, the next module cleans up the Audit Trail for better efficiency in later stages, removing irrelevant entries from the dataset. At the same time, the relevant feature for each Audit Trail entry, such as *extrude 5* or *revolve 2,* is also appended to each entry in the .csv file to aid with troubleshooting should the need arise. Next the Audit Trail is analyzed, and the event plot is generated. The sequence of actions taken by the participant is coded and added to a central database, which can then be used to train the hidden Markov model.

7.6 CAD Actions Visualization

Looking at raw data logs of CAD usage and detecting any meaningful patterns can be quite challenging. Inspired by Atman's work in visualizing the engineering design processes [14], we explored the possibility of generating event plots to visualize our Audit Trail data in a similar manner to aid with analyzing and making sense of our collected data.

Figure 29 is an example of an event plot of a participant's actions:

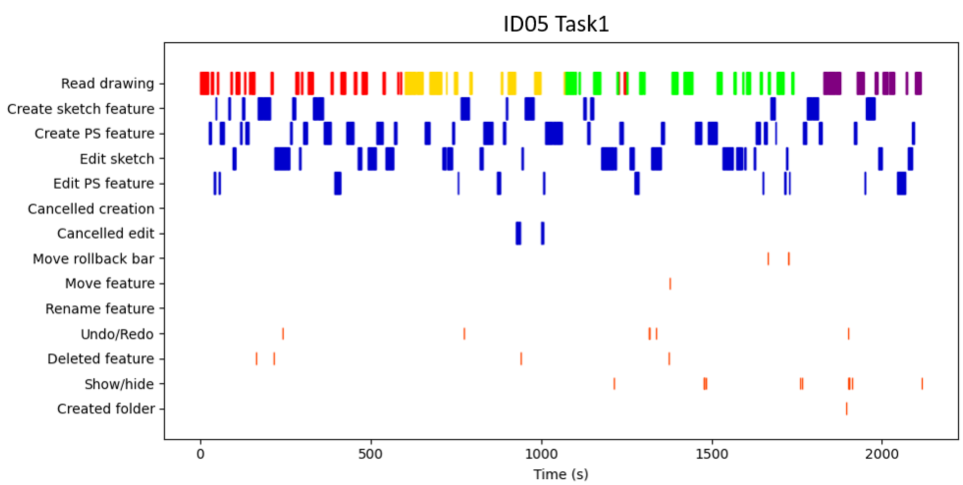


Figure 29 Plotting Participant's Actions in the Form of an Event Plot

The top half of the diagram plots the actions in the first group discussed in section 7.4, where the length of the individual bars corresponds to the amount of time spent. The bottom half of the diagram plots the group 2 actions. Each event instance is plotted as an orange bar of a fixed width.

The top "Read Drawing" row shows all the times a participant spent reading the instruction drawings and includes four colors, corresponding to the four steps in CAD task (Step 1 – Red, Step 2 – Yellow, Step 3 – Green, Step 4 – Purple). This allows us to easily see the progress for each participant, as well as determine if a participant has had to refer to an earlier step, as may happen when someone goes back in the feature tree and fix an earlier error.

Our initial hypothesis was that there might be visually discernable differences in the plots of high performing and low performing participants, but initial results show that is not the case. This is likely due to the large differences between each participant's preferences, CAD habits, and modelling style. However, we were still able make a few interesting observations while studying the participants' event plots.

7.6.1 Evidence of Forward Planning

One observation is that a subset of the participants' event plots exhibits a colorful segment on the "read drawing" row near the start of the session (shown in Figure 30) which happens when participants look ahead at all the drawings at the start before beginning to model. We see that generally the more experienced CAD users exhibit this behaviour, as they try to mentally construct the final model and plan their modelling approach accordingly. Some participants explicitly stated this as a strategic move during the interviews. This behavior was evident in some of the lower performing participants as well, so we were unable to attribute high CAD performance to this practice directly.

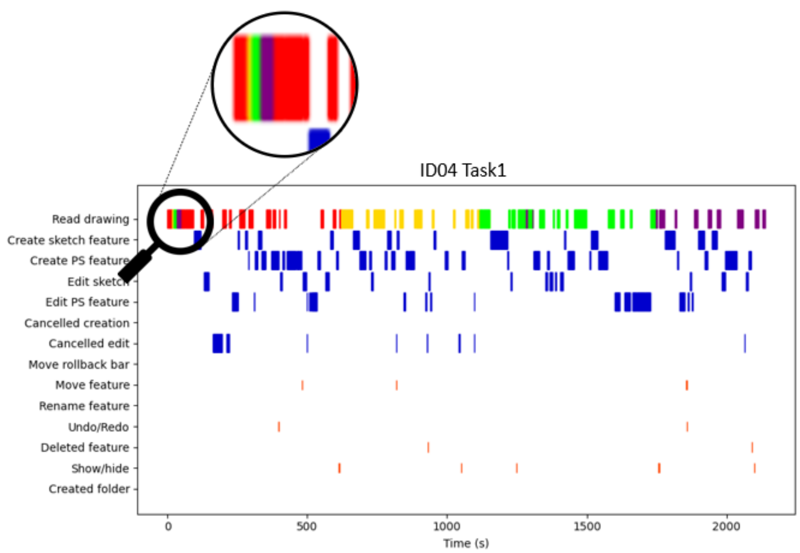


Figure 30 Sign of Participant Planning Ahead Evidenced by Drawing Viewing Activity

7.6.2 Methodical vs Disorganized Modelling

Highly experienced users are generally able to formulate a plan and take a systematic approach to creating CAD models, often seeking out additional opportunities for optimizations or building in additional flexibility. In contrast, less experienced CAD users may opt to take a more trial-and-error approach, opting to build one feature at a time and make edits as the need arises. In Figure 31 we show a contrasting pair of participant event plots. Participant ID01 (top) is a seasoned mechanical engineer with many years of experience as a product designer. Participant ID02 (bottom) is first year undergraduate mechanical engineering student with much less CAD experience. We can make a few observations from comparing these two charts.

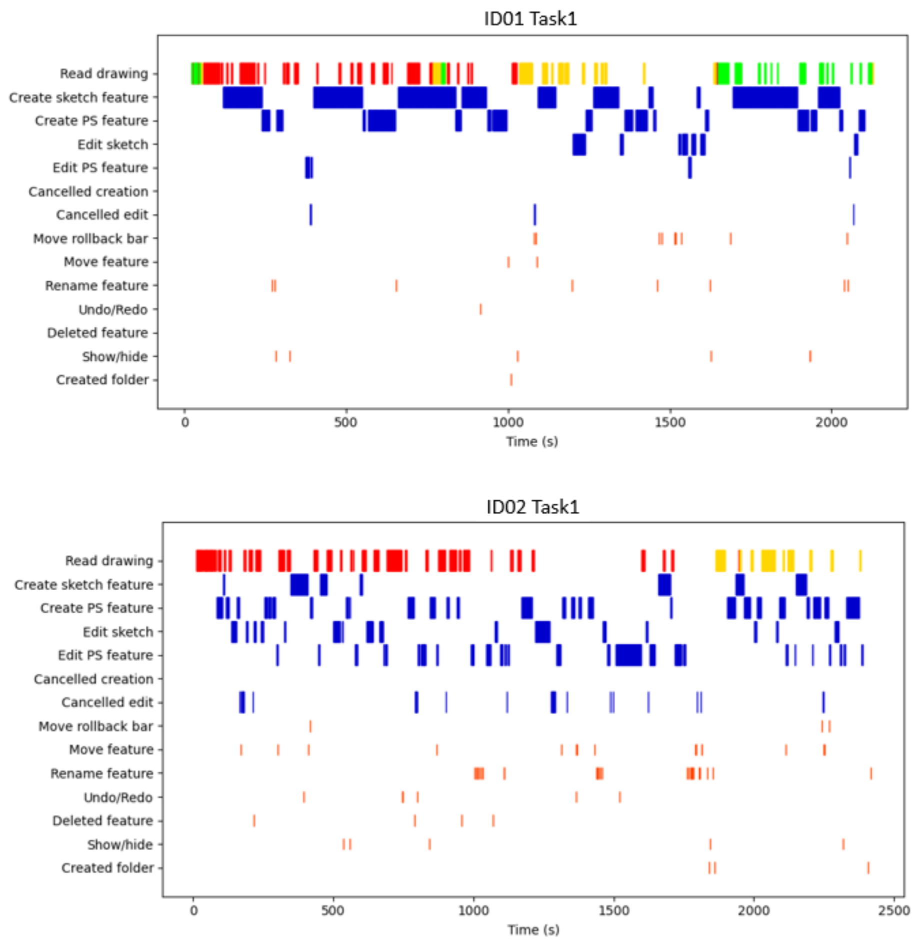


Figure 31 Visualization of Methodical (top) vs Disorganized (bottom) Approaches

We see that visually, the actions of participant 1 follow a relatively consistent pattern; typically beginning with “create sketch feature”, as expected, then advancing to “create part studio feature”. Towards the latter half, a few more editing of existing sketches started to appear. We also see that “move rollback bar” instances mostly line up with periods of editing. Reviewing the video footage shows that participant 1 used the rollback bar to step back in time to edit earlier features and effectively manage the interdependencies between features. Lastly, we can notice that the user regularly renamed key features with descriptive names throughout the entire process. This helped to identify the relationship between features and improve the organization of the model.

In contrast, when we look at the bottom plot of participant 2’s actions, we observe a much more chaotic progression. During the experiment, participant 2 regularly reverted to edit earlier features to fix mistakes. Model regeneration errors also occurred multiple times, often when the participant decided to change his approach. Frequent changes in his modelling strategy also required multiple features to be edited and reordered on the feature tree, as evident in the sudden bursts of “move feature” and “rename feature” entries on the diagram. We also observe a total of four feature deletions, compared to zero for participant 1. This is similar to the findings in Bhavnani’s study showing novice CAD users preferring to delete features and redo instead of making edits [28]. However, this behaviour was not consistently observed in our novice participants.

7.6.3 Signs of Inexperience in Modelling

Event plots can also help identify when a user struggles to complete a task during CAD modelling. Figure 32 shows an example of a participant who struggled to make progress during the experiment. As evident in the event plot, we see that the user spent most of the experiment creating and editing sketch features. There is also a distinct lack of diversity in the event plot in terms of observed action types. Observations made during the experiment noted that the participant faced significant challenges in creating the desired sketch geometries and setting the correct geometrical constraints.

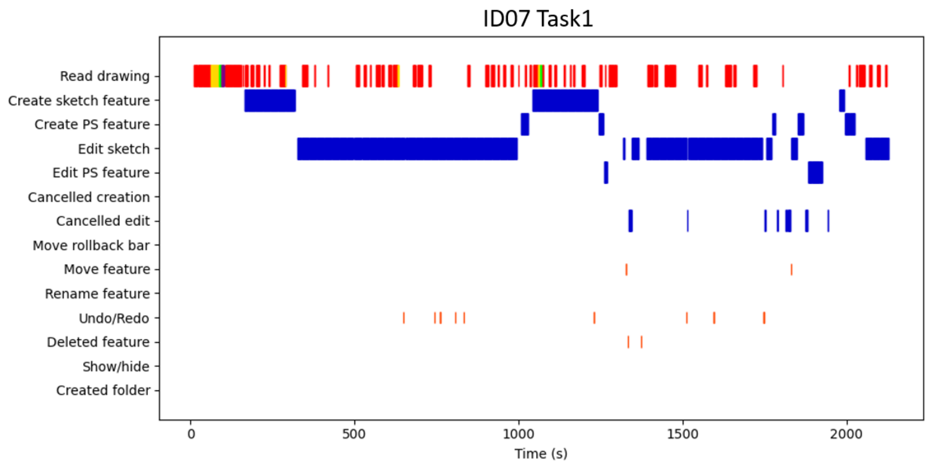


Figure 32 Event Plot of a User Showing Signs of Struggle

Situations like these highlight the limitations noted earlier regarding Audit Trails, that they do not capture enough information to clarify the exact difficulties a user is facing. Nevertheless, in educational settings, Audit Trail analysis and event plots could still help identify those who are struggling and allow educators to offer more individualized help. A student's Audit Trail sequence could be used to pinpoint which features were the most problematic. With these new tools, CAD education and training have the potential to be much more effective.

7.6.4 Future Explorations with Event Plots

Representing the raw Audit Trail data visually allows us to better identify and highlight patterns within people's actions. It also helps us understand what experts do well or differently from those less experienced. As evidenced in this study, identifying clear, consistent patterns within CAD users' actions is challenging. The nature of the assigned task will also strongly affect the sequences and patterns of actions as well. We hope to combine additional sources of data to allow event plots to deliver greater value in the future.

7.7 Hidden Markov Modelling

We explored another method of analyzing the actions of participants, through hidden Markov modelling (HMM). Hidden Markov models have been used in many applications, including gene recognition, speech recognition, sequence classification, time series analysis, and designer actions [41][42][25]. McComb et al. have shown in their experiment that hidden Markov models can be effective in describing design processes and can be used to discover procedural differences between high- and low-performing designers [25].

In hidden Markov modelling, we treat the system of interest as having a set of hidden discrete states that cannot be directly observed. The system transitions between the discrete states at instances in time, with the probability from transitioning from one state to another defined by the transition probability matrix. Each time the system transitions to a different hidden state, it is assumed that one observable emission will be released, as shown visually in Figure 33. Each hidden state has a probability distribution associated with a set of possible emissions, so certain observations may be more strongly associated with certain hidden states. By studying the observations, we aim to understand the underlying structure of our system, the transition behavior between the hidden states, and the relationships between emissions and hidden states.

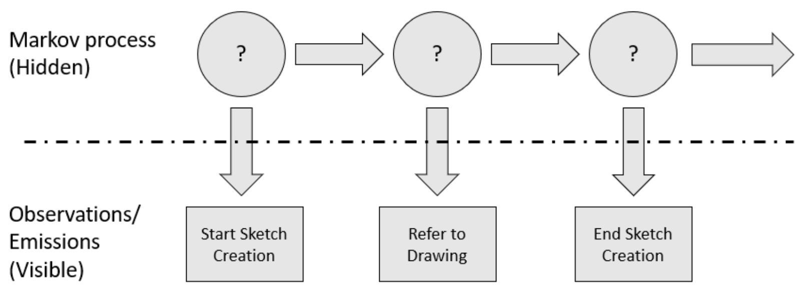


Figure 33 Representation of the Hidden States and the Visible Observations

Here, we use hidden Markov modeling to study the differences in transition behavior between the expert participants and the intermediate participants, as well as attempt to infer the higher-level mental states of the users during modelling.

7.7.1 Audit Trail Coding (Observations)

We first begin by collecting the study participants' sequence of actions and binning them into seven operation categories. These seven operations serve as the set of possible observations for the hidden states. Table 5 summarizes the relevant actions within each category.

Table 5 The Seven Operation-types for Coding All User Actions

Operation	Code	Relevant Actions
Refer to Drawing	0	Open drawing
Start creation	1	Begin creation of a new feature or sketch
End creation	2	Confirm a new feature or sketch
Start edit	3	Begin edit of an existing feature or sketch
End edit	4	Confirm changes to an existing feature or sketch
Delete	5	Delete a sketch or feature
Organize	6	Move a feature Rename a feature Create a folder

Our Python script analyzes each participant's Audit Trail and generates a string of coded values representing the sequence of their actions from start to finish during the study. We create four separate datasets to contain all the combined sequences of the expert participants' first and second tasks, and two more for the intermediate participants. These four datasets are given as input to our hidden Markov models during training. Table 6 presents the number of data points within each of the combined datasets.

Table 6 Number of Data Points within Each Combined Dataset

Dataset	Number of data points
Experts Task 1	1868
Experts Task 2	797
Intermediates Task 1	1245
Intermediates Task 2	530

7.7.2 Determining Optimum Number of Hidden States

Next, we can move onto training our hidden Markov model by using the observations to estimate the HMM parameters and the transition and emission probabilities. However, we are presented with a dilemma. Training a hidden Markov model requires the number of hidden states to be known, but given the exploratory nature of this study, we were unaware what the optimal number of hidden states could be. In this study, we opted to train multiple models with the number of hidden states ranging from 1 to 7 and comparing the testing log likelihoods for each to determine what value produced a model that best fits our dataset. The results are plotted as shown in Figure 34. Training hidden Markov models beyond seven states is unnecessary as the emission probabilities of the states cease to be linearly independent when we have more states than emissions. For each number of hidden states, we train 10 iterations of the model to prevent settling on a local maximum.

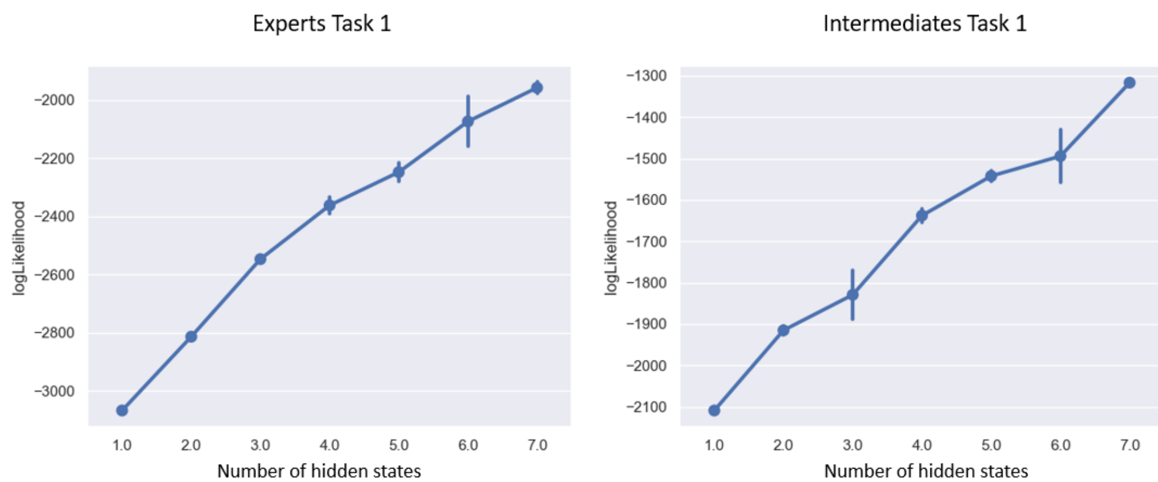


Figure 34 Testing log Likelihood on Experts and Intermediates study data.

Here, we are faced with another challenge. As we can see in Figure 34, increasing the number of hidden states continually increases the log likelihood of the model. Only using model log likelihood as a metric can lead us to overfitting, erroneously selecting too many hidden states. As Przytycka cautioned, lack of data leads to overfitting of the model [42]. Given we have a relatively small dataset, this seems likely to be the case.

To correct for this error, we also calculated the BIC (Bayesian Information Criterion) for each number of hidden states. BIC attempts to resolve the problem of overfitting by introducing a penalty term for the number of parameters in the model, essentially acting as a counterbalance for adding model complexity [43]. As we increase the number of hidden states, the number of model parameters also increase, which drives up the BIC. The model with the lowest BIC therefore, represents the best balance between the model's complexity and goodness of fit. Again, we trained 10 separate iterations for each value of hidden states. As we can see in Table 7, four appears to be the optimum number of hidden states for both datasets.

Table 7 Average Model BIC Values for Different Number of Hidden States

Hidden States	BIC (Experts)	BIC (Intermediates)
1	6186.5	4267.7
2	5769.4	3965.6
3	5402.0	3950.9
4	**5318.7**	**3838.9**
5	5542.4	4075.4
6	5857.1	4606.5
7	6543.1	5121.0

7.7.3 Expert Dataset HMM Results

We first look at the results of the 4-state hidden Markov model trained with the experts dataset. Figure 35 shows the transition (left) and emission (right) matrices of the HMM. The numbers within the cells indicate the transition or emission probabilities, and the cells are coloured according to their values. Larger values correspond to higher probabilities. For example, based on the emissions matrix on the right, we can see that the most likely action a user will take while in state 1 is “Start Create”, with a 68% probability.

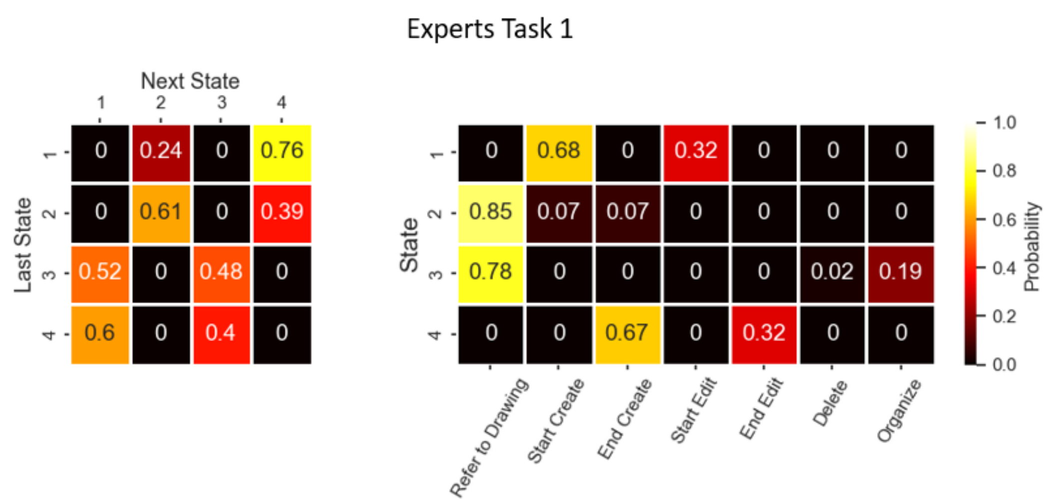


Figure 35 Transition (left) and Emission (right) Matrices For the 4-state Hidden Markov Model Based on the Experts Task 1 Data

Interpreting these matrices, we see that state 1 corresponds to the beginnings of feature creation or editions, evident by its two possible emissions of “Start Create” and “Start Edit”. Observing the transition matrix, we see a user is most likely to transition from state 1 to 4, with a 76% probability, along with a 24% probability of transitioning from state 1 to 2 instead. State 2 is dominated by “refer to drawing” as the main emission and tends to be followed by state 2 again or 4 as the next state.

We can see that the logical sequences of actions during the modelling of “Start create/edit” → “Refer to Drawing” → “End create/edit” or “Start create/edit” → “End create/edit” (in the case where the participant does not have to refer to the drawing midway) are both well represented by the state transition probabilities. The first sequence maps to a state transition sequence of 1→2→4 and the latter 1→4.

Next, we look at the transition probabilities from state 4. There is a 60% chance of progressing to state 1 and a 40% chance of transitioning to state 3, whose emissions are primarily “refer to drawing”, and to a smaller extent “organize”. This matches with our experimental observations. A state 4→1 transition represents the user moving forward during the experiment to create another feature, whereas a state 4→3 transition corresponds to the participant either referring to the drawing or re-organizing the model before forging ahead. The relatively low emission probability of 19% for “organize” in state 3 also appears reasonable, since most users perform those actions infrequently during the study.

We can create a visual representation of the transition and emission probabilities to summarize all the information presented in the two matrices, presented in Figure 36. The values beside each arrow denote the probability of transitions between states, while the italicized values represent the emissions probabilities while at each state. The hidden states are represented as circles and the emissions are represented with rectangles. Note that emissions with low probabilities are omitted to prevent cluttering.

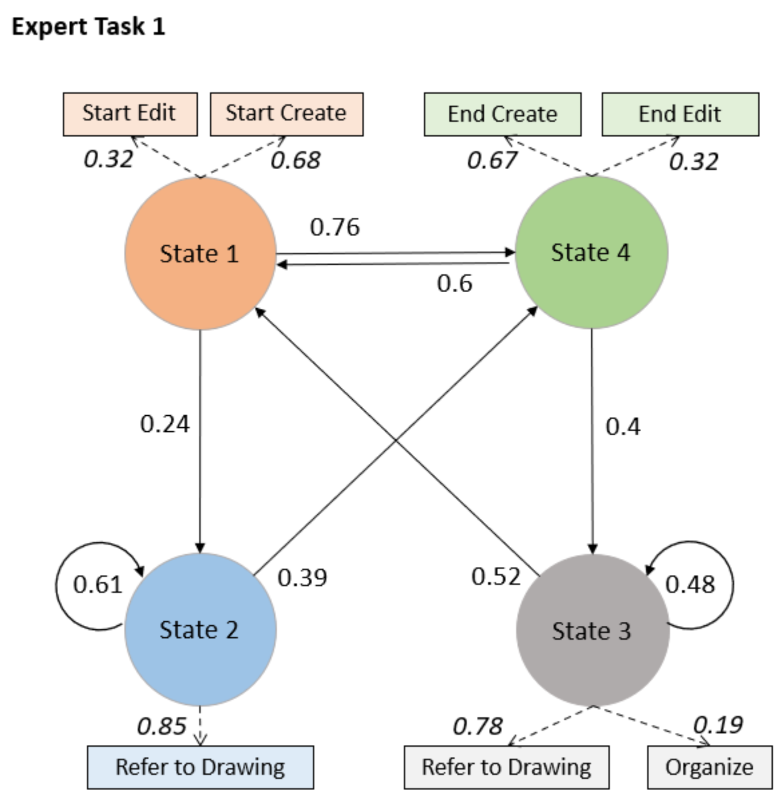


Figure 36 Visual Representation of HMM Trained on Experts Dataset

Interestingly, the HMM allows us to make a distinction between two kinds of read-drawing actions. State 2's "Refer to Drawing" represents when the user looks at a drawing midway through feature creation or edition, perhaps to look for the dimension of a feature or a certain geometry. We see that there is no probability of transitioning from 1 directly to 3. This means the "refer to drawing" action that happens at state 3 is after someone has finished a feature; where the person is looking for information on the next feature to create or looking at the overall structure of the model to plan the logical next move. This is a good demonstration of hidden Markov models' ability to provide insights from analyzing sequences of observations.

7.7.4 Intermediate Dataset HMM Results

We carried out the same analysis for the dataset containing all the modelling sequences of intermediate participants and noticed a few differences when compared to the expert HMM model. Looking at Figure 37 and Figure 38, we see that all states now have some probability of emitting "refer to drawing". Two states (2 and 3) now also have probability of emitting "organize", whereas the organizational actions are confined to one state for the experts.

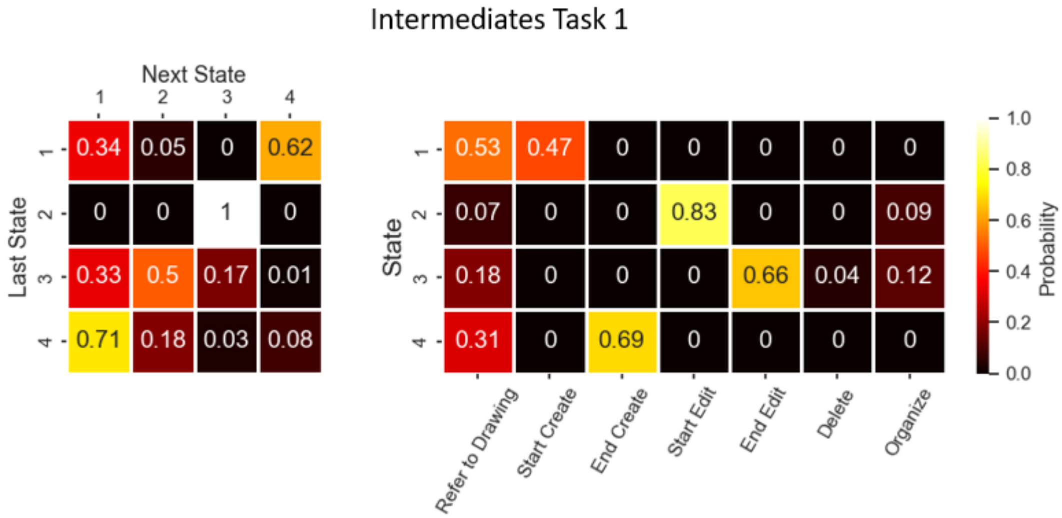


Figure 37 Transition (left) and Emission (right) Matrices For the 4-state Hidden Markov Model Based on the Intermediates Task 1 Data

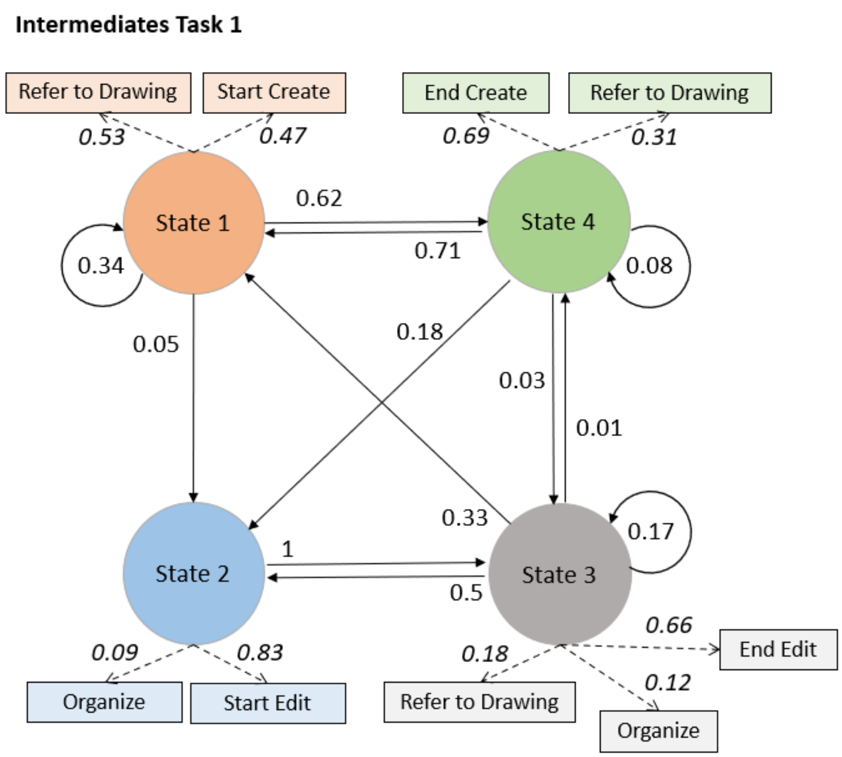


Figure 38 Visual Representation of HMM Trained on Intermediates Dataset

In this model, states 1, 3, and 4 are all have a probability to emit "Refer to Drawing". This may suggest that intermediate participants tended to refer to the drawings more often during feature creation and edition. Subjective observations made during the experiments note that some of the intermediate participants less versed in reading drawings or creating CAD models referred to the drawing more, as they were less able to systematically capture information and remember details at each glance. The hidden Markov model results seem to provide some evidence for those subjective observations.

We also note that “Start Create”, “End Create”, “Start Edit”, and “End Edit” are now spread across four states, a stark contrast to the Experts’ HMM model. This suggests that there may be larger differences between feature creation and edition for intermediate participants when compared to the expert users. This could be explained by the fact that the intermediate users tended to make features that are less well-defined, requiring multiple iterations of editing.

The overlapping of the same emissions for several states as well as the more varied state transitions may be a manifestation of the less organized modelling flow of the intermediate participants, where they often switch back and forth between creating new features and fixing old mistakes. Looking at the transition probabilities, we see that it is very likely to switch between states 1 and 4, and similarly between states 2 and 3, but it is much less likely to transition between the two pairs of states. One explanation is that intermediate participants spend less effort planning ahead (or lack the foresight to do so) and they tend to create multiple features in bursts. We know that in CAD modelling ill-defined model geometries early on can often cause cascading errors later, where one small mistake causes a whole chain of features to fail. During modelling, if and when errors do crop up for intermediate participants, they often have to edit multiple features to fix the mistakes since their original model sequence or approach was less thought-out, leading to the transitional probabilities we observe in the HMM.

7.7.5 Task 2 HMM Results

We repeated the same process to analyze the actions taken during the second experimental task for both groups and present the results in Figure 39. Calculating the BIC led us to hidden Markov models with three hidden states instead of four, likely due to fact that the patterns of actions during Task 2 have much less variation. The typical sequences of actions during Task 2 are “Start edit” → “Refer to Drawing” → “End edit” and “Refer to Drawing” → “Start create/edit” → “End create/edit”, both of which are very well captured by the HMM models for both groups as shown in Figure 39. We observe that one state is mostly concerned with “Refer to Drawing”, a second state dominated by “Start Edit”, and the last state with “End Edit” as its highest probability.

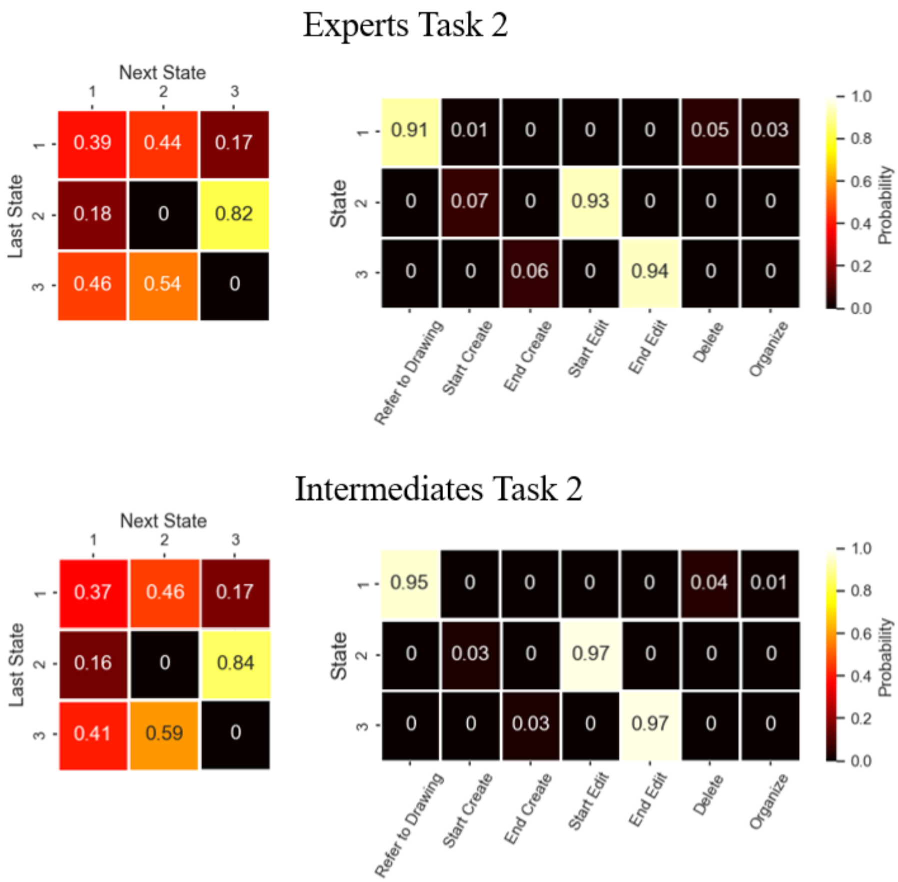


Figure 39 Task 2 HMM Results for Both Groups

These results match our expectations as we observed most participants were able to make the required changes with relative ease during the second task, and their actions matched the sequences evident in the HMM. In the cases where more extensive changes were required, we observed participants creating entirely new features, deleting existing features, or reorganizing the feature tree, which explains the non-zero emission probabilities for these actions.

It is also interesting that the HMM results for both experts and intermediates are remarkably similar for Task 2, when it was not the case for Task 1. We suspect this could be due to the lower difficulty involved in Task 2, therefore there were little to separate the experts and the intermediates. This could also signal that editing models is a less cognitively demanding task, especially when editing one’s own model that was made very recently. As such, CAD training could include more editing tasks to provide more sense of achievement and variety.

As discussed in Section 3.1, the motivation for Task 2 was to provide an opportunity for self-assessment and study CAD user actions while working on a task focused more on making edits instead of creating new features. While the HMM results matched our expectations, it is clear that we were unable to gather deeper insight into the thought process of a CAD user during an editing task due to the resolution of our dataset. More detailed categorization of actions and longer tasks focused on editing models in the future may offer more insights.

8 Conclusions and Future Work

8.1 Conclusions

We have successfully developed a novel experimental protocol that utilizes Onshape as a design study platform to conduct CAD design experiments. The protocol was tested and validated through a series of experiments with a total of 19 recruited participants. Leveraging the Audit Trail feature allowed us to efficiently extract and analyze participants' CAD actions during the experiment without the need to go through the time-consuming process of manual coding. This experimental protocol is easily scalable since data processing is highly automated through a series of python scripts.

It was found that while the second experimental task did succeed in prompting some participants to identify weaknesses in their initial modelling approaches, in general it yielded much less useful data and insight compared to the first experimental task. If the complexity and scope of the first design task was increased, and participants were given more time, the natural iterations of design cycles may be able to capture the type of editing behaviour Task 2 was designed to elicit. In which case, we would be able to eliminate Task 2 from the experiment entirely.

In our study, we found the determination of participant CAD skill level difficult, especially in the absence of some form of standardized assessment. Self-reported CAD expertise levels were shown to be poor indicators of actual CAD performance. Future iterations of the experimental protocol would benefit from the addition of some form of competency evaluation to provide a baseline for all participant comparisons.

The interviews conducted during the experiment sessions yielded a few key findings. Using layout sketches, creating robust references, and staying adaptable while modelling are the key takeaways to success according to our experts. Given the time required to conduct these interviews, future iterations of the experiment protocol may benefit from reducing the length of the interviews and allocating the time towards modelling tasks instead.

The visualizations of participants' CAD actions in the form of event plots were not always visually substantially different between high and low-performing participants as we had envisioned. However, we were still able to utilize event plots to identify some patterns of modelling organizational behaviour as well as evidence of forward planning. Event plots with more detailed categories or plotted over a longer duration may reveal larger patterns that were not present in our short experimental study.

Lastly, through hidden Markov modelling we were able to identify some differences between the intermediate and expert participants. The preliminary results demonstrated the exciting potential of hidden Markov models' ability to uncover higher-level mental states simply through analyzing sequences of user actions without any prior knowledge. Future implementations of HMM for CAD design experiments could be greatly improved with more complex coding schemes and larger datasets.

8.2 Limitations

As discussed earlier, a major limitation of the Audit Trail structure precludes us from gaining insight into the actions taken during feature definition, which is admittedly an important aspect of modelling that we are blind to when implementing this methodology. The effect of this drawback can be lessened by focusing on CAD sessions with longer time horizons and studying larger design cycle patterns. This could be achieved by collecting Audit Trails for semester-long projects or large design projects with multiple design iterations, for example.

Our experimental methodology of assigning a prescribed task to the participants does not fully reflect how CAD is typically used in practice. As such, the data we collected may only represent a subset of the possible actions people may take during modelling. In order to capture a wider range of behaviours, future experiments should provide a much more open-ended task for the participants to work on.

Lastly, as some participants have mentioned in their interviews, having a time limit during the experiment added additional stress that some participants may not be familiar with while modelling. As an alternative solution, we could look for opportunities to collect Audit Trail data from existing design projects, where we can be sure the CAD users were able to work under their preferred environments.

8.3 Future Work

Additional forms of CAD action visualization should be explored, such as cumulative and progressive time plots [40], or stacked event plots of a particular action type for multiple participants to more easily visualize any potential differences between people and trends.

In this paper we created event plot visualizations using the full duration of the experimental tasks. Isolating and further analyzing specific portions or segments could provide additional insight into the CAD users' thought process. Combined with other data sources such as the video recordings, we may be able to better match specific series of actions with certain modelling intents.

For more in-depth hidden Markov modelling, additional action types could be included in the analysis as emissions, such as accounting for the types of features created or edited during each creation or edition cycle. Capturing more modelling actions and types could help uncover the higher-level mental states of CAD users more accurately. Our study showed that different types of tasks can have a large impact on the HMM results. It would be worthwhile to prescribe experimental tasks with different goals, analyze them separately, and study the difference in the results obtained.

Another progression for the current experiment protocol is to include multi-body modelling, assembly modelling, as well as multi-user collaboration as experimental tasks over longer time horizons. That will greatly increase the diversity of actions available to be captured. CAD modelling is rarely a solitary endeavor in engineering, capturing the interactions and effects of collaborative modelling scenarios would yield highly valuable results. With larger datasets, there is the opportunity to leverage the tools we have developed here to identify different users' CAD modelling styles, which could help designers work together more effectively.

In this study we focused primarily on the actions of each participant through the Audit Trails. A logical next step would be to study the CAD models each participant made during the experiment to identify strategies that were effective or common mistakes made by less-experienced CAD users, as well as how each participant inferred the design intent and implemented them while creating the model. With the help of Onshape's API, a portion of this analysis could be done automatically. The parameters and dimensioning schemes of each participant's model could be extracted from the API response and tabulated or checked against expected values. Automated analysis of models and design intent could prove highly useful in training and educational settings.

With a large enough dataset of CAD user actions, the concept of an adaptive CAD system could also be explored, where the system is able to anticipate the user's next actions or infer the user's next likely feature based on their previous sequence of activity [28]. A system like this could also be used to help new CAD users by prompting suggestions or providing guidance to the user when appropriate.

Lastly, expanding our methodology to incorporate the multimodal information is an extremely exciting prospect. Combination of facial emotion tracking, brain pattern imaging, or eye tracking with designer actions in CAD could help us delve deeper into the complex thought processes that drive CAD modelling and discover new insights.

References

[1] Y. Bodein, B. Rose, and E. Caillaud, “Explicit reference modeling methodology in parametric CAD system,” *Comput. Ind.*, vol. 65, no. 1, pp. 136–147, 2014, doi: 10.1016/j.compind.2013.08.004.

[2] Y. Bodein, B. Rose, and E. Caillaud, “A roadmap for parametric CAD efficiency in the automotive industry,” *CAD Comput. Aided Des.*, vol. 45, no. 10, pp. 1198–1214, 2013, doi: 10.1016/j.cad.2013.05.006.

[3] A. Rynne and W. Gaughran, “Cognitive modelling strategies for optimum design intent in parametric modelling (PM),” *ASEE Annu. Conf. Expo. Conf. Proc.*, no. January 2007, 2007.

[4] J. D. Camba, M. Contero, and P. Company, “Parametric CAD modeling: An analysis of strategies for design reusability,” *CAD Comput. Aided Des.*, vol. 74, pp. 18–31, 2016, doi: 10.1016/j.cad.2016.01.003.

[5] A. Rynne, W. F. Gaughran, and N. Seery, “Defining the variables that contribute to developing 3D CAD modelling expertise,” *Graph. Model. Int. Conf. Des. Technol. Educ. Res. Curric. Dev.*, pp. 161–183, 2010.

[6] G. T. Lang, R. E. Eberts, M. M. Barash, and M. G. Gabel, “Extracting and Using Procedural Knowledge in a CAD Task,” *IEEE Trans. Eng. Manag.*, vol. 38, no. 3, pp. 257–268, 1991, doi: 10.1109/17.83758.

[7] I. Chester, “3D-CAD : modern technology – outdated pedagogy?,” *Des. Technol. Educ. An Int. J.*, vol. 12, no. 1, pp. 7–9, 2007.

[8] R. F. Hamade, H. A. Artail, and M. Y. Jaber, “Evaluating the learning process of mechanical CAD students,” *Comput. Educ.*, vol. 49, no. 3, pp. 640–661, 2007, doi: 10.1016/j.compedu.2005.11.009.

[9] H. E. Otto and F. Mandorli, “Parametric feature-based solid model deficiency identification to support learning outcomes assessment in CAD education,” *Comput. Aided. Des. Appl.*, vol. 18, no. 2, pp. 411–442, 2020, doi: 10.14733/cadaps.2021.411-442.

[10] X. Garikano, M. Garmendia, A. P. Manso, and E. Solaberrieta, “Strategic knowledge-based approach for CAD modelling learning,” *Int. J. Technol. Des. Educ.*, vol. 29, no. 4, pp. 947–959, 2019, doi: 10.1007/s10798-018-9472-1.

[11] M. H. Rahman, C. Schimpf, C. Xie, and Z. Sha, “A Computer-Aided Design Based Research Platform for Design Thinking Studies,” *J. Mech. Des.*, vol. 141, no. 12, pp. 1–12, 2019, doi: 10.1115/1.4044395.

[12] J. Gopsill, C. Snider, L. Shi, and B. Hicks, “Computer aided design user interaction as a sensor for monitoring engineers and the engineering design process,” *Proc. Int. Des. Conf. Des.*, vol. DS 84, pp. 1707–1718, 2016.

[13] K. Kitajima, K. Oikawa, and T. Murakami, “Study on Feature Analysis of CAD Operation Log and Its Application,” *ICDES 2020 5th Int. Conf. Des. Eng. Sci.*, no. November 2020, pp. 33–41, 2021.

[14] C. J. Atman, R. S. Adams, M. E. Cardella, J. Turns, S. Mosborg, and J. Saleem,

"Engineering design processes: A comparison of students and expert practitioners," *J. Eng. Educ.*, vol. 96, no. 4, pp. 359–379, 2007, doi: 10.1002/j.2168-9830.2007.tb00945.x.

[15] J. Buckley, N. Seery, and D. Canty, "Heuristics and CAD modelling : an examination of student behaviour during problem solving episodes within CAD modelling activities," *Int. J. Technol. Des. Educ.*, vol. 28, no. 4, pp. 939–956, 2018, doi: 10.1007/s10798-017-9423-2.

[16] E. Ozturk, B. Yalvac, M. Johnson, X. Peng, and K. Liu, "Adaptive Expertise and its Manifestation in CAD Modeling: A Comparison of Practitioners and Students," *122nd ASEE Annu. Conf. Expo.*, pp. 26.155.1-26.155.14, 2015, doi: 10.18260/p.23494.

[17] R. F. Hamade, "Profiling the desirable CAD trainee: Technical background, personality attributes, and learning preferences," *J. Mech. Des. Trans. ASME*, vol. 131, no. 12, pp. 1210091–12100910, 2009, doi: 10.1115/1.4000455.

[18] A. Hamlin, N. Boersma, and S. Sorby, "Do spatial abilities impact the learning of 3-D solid modeling software?," *ASEE Annu. Conf. Expo. Conf. Proc.*, 2006, doi: 10.18260/1-2--1272.

[19] T. J. Branoff and M. Dobelis, "Relationship between students' spatial visualization ability and their ability to create 3D constraint-based models from various types of drawings," *ASEE Annu. Conf. Expo. Conf. Proc.*, no. December, 2014, doi: 10.18260/1-2--22971.

[20] T. Delahunty, N. Seery, R. Dunbar, and M. Ryan, "An exploration of the variables contributing to graphical education students' CAD modelling capability," *Int. J. Technol. Des. Educ.*, vol. 30, no. 2, pp. 389–411, 2020, doi: 10.1007/s10798-019-09503-x.

[21] T. Kösa and F. Karakuş, "The effects of computer-aided design software on engineering students' spatial visualisation skills," *Eur. J. Eng. Educ.*, vol. 43, no. 2, pp. 296–308, 2018, doi: 10.1080/03043797.2017.1370578.

[22] S. A. Sorby, "Spatial abilities and their relationship to effective learning of 3-D solid modeling software," *Eng. Des. Graph. J.*, vol. 64, no. 3, pp. 30–35, 2000.

[23] S. A. Sorby, "Educational research in developing 3-D spatial skills for engineering students," *Int. J. Sci. Educ.*, vol. 31, no. 3, pp. 459–480, 2009, doi: 10.1080/09500690802595839.

[24] C. Xie, Z. Zhang, S. Nourian, A. Pallant, and E. Hazzard, "Time series analysis method for assessing engineering design processes using a CAD tool," *Int. J. Eng. Educ.*, vol. 30, no. 1, pp. 218–230, 2014.

[25] C. McComb, J. Cagan, and K. Kotovsky, "Mining Process Heuristics from Designer Action Data Via Hidden Markov Models," *J. Mech. Des. Trans. ASME*, vol. 139, no. 11, pp. 1–12, 2017, doi: 10.1115/1.4037308.

[26] C. Mccomb, J. Cagan, and K. Kotovsky, "Utilizing Markov Chains to Understand Operation Sequencing in Design Tasks," *Des. Comput. Cogn.*, 2016, doi: 10.1007/978-3-319-44989-0.

[27] C. Mccomb, J. Cagan, and K. Kotovsky, "Capturing Human Sequence- Learning Abilities in Configuration Design Tasks Through Markov Chains," *J. Mech. Des.*, vol. 139, no. September, pp. 1–12, 2017, doi: 10.1115/1.4037185.

[28] S. Bhavnani, J. Garrett Jr, and D. Shaw, "Leading Indicators of CAD Experience," *5th Int. Conf. Comput. Archit. Des. Futur.*, pp. 313–334, 1993.

[29] M. F. Daud, J. M. Taib, and R. S. Shariffudin, "Assessing Mechanical Engineering Undergraduates ' Conceptual Knowledge in Three Dimensional Computer Aided Design," vol. 56, no. Ictlhe, pp. 1–11, 2012, doi: 10.1016/j.sbspro.2012.09.626.

[30] H. K. Ault and A. Fraser, "A comparison of manual vs. Online grading for solid models," *ASEE Annu. Conf. Expo. Conf. Proc.*, 2013, doi: 10.18260/1-2--19045.

[31] D. H. Baxter and M. J. Guerci, "Automating an introductory computer aided design course to improve student evaluation," *ASEE Annu. Conf. Proc.*, pp. 6503–6510, 2003, doi: 10.18260/1-2--11479.

[32] J. Kruger and D. Dunning, "Unskilled and unaware of it: how difficulties in recognizing one's own incompetence lead to inflated self-assessments," *J. Pers. Soc. Psychol.*, vol. 77, no. 6, pp. 1121–1134, 1999, doi: 10.1037//0022-3514.77.6.1121.

[33] B. Stone *et al.*, "A multi-user computer-aided design competition: Experimental findings and analysis of team-member dynamics," *J. Comput. Inf. Sci. Eng.*, vol. 17, no. 3, pp. 1–10, 2017, doi: 10.1115/1.4035674.

[34] X. Peng, P. McGary, M. D. Johnson, B. Yalvac, and E. Ozturk, "Assessing Novice CAD Model Creation and Alteration," *Comput. Aided. Des. Appl.*, vol. PACE, no. 2, pp. 9–19, 2012, doi: 10.3722/cadaps.2012.pace.9-19.

[35] C. M. Hoffman and R. Joan-Arinyo, "CAD and the Product Master Model," *CAD Comput. Aided Des.*, vol. 30, no. 11, pp. 905–918, 1998, doi: 10.1016/S0010-4485(98)00047-5.

[36] Onshape, "Onshape Enterprise Analytics - Audit Reports," *Audit Reports*. https://cad.onshape.com/help/Content/audit_reports.htm?tocpath=Enterprise%7CAccessing Analytics (accessed Aug. 10, 2021).

[37] V. Phadnis, H. Arshad, D. Wallace, and A. Olechowski, "Are Two Heads Better Than One For Computer-Aided Design?," *J. Mech. Des.*, vol. 143, no. July, pp. 1–38, 2021, doi: 10.1115/1.4050734.

[38] J. J. Zhou, V. Phadnis, and A. Olechowski, "Analysis of Designer Emotions in Collaborative and Traditional Computer-Aided Design," *J. Mech. Des. Trans. ASME*, vol. 143, no. 2, pp. 1–10, 2021, doi: 10.1115/1.4047685.

[39] Y. T. Shih and W. Sher, "Exploring the Role of CAD and its Application in Design Education," *Comput. Aided. Des. Appl.*, vol. 18, no. 6, pp. 1410–1424, 2021, doi: 10.14733/cadaps.2021.1410-1424.

[40] C. J. Atman, K. Deibel, and J. Borgford-Parnell, "The Process of Engineering Design: A Comparison of Three Representations," *ICED 09*, pp. 483–494, 2009.

[41] I. Votsi, N. Limnios, E. Papadimitriou, and G. Tsaklidis, "Hidden Markov Models."

[42] T. M. Przytycka and J. Zheng, "Hidden Markov Models," *eLS*, 2011, doi: 10.1002/9780470015902.a0005267.pub2.

[43] G. Schwarz, "Estimating the Dimension of a Model," *Ann. Stat.*, vol. 6, no. 2, pp. 461–464, 1978, [Online]. Available: https://projecteuclid.org/journals/annals-of-

statistics/volume-6/issue-2/Estimating-the-Dimension-of-a-Model/10.1214/aos/1176344136.full.

[44] Too Tall Toby, *TooTallToby's 3D CAD TOURNAMENT - June 2020 https://www.youtube.com/watch?v=PjAOmK_MUgc*. YouTube, 2020.

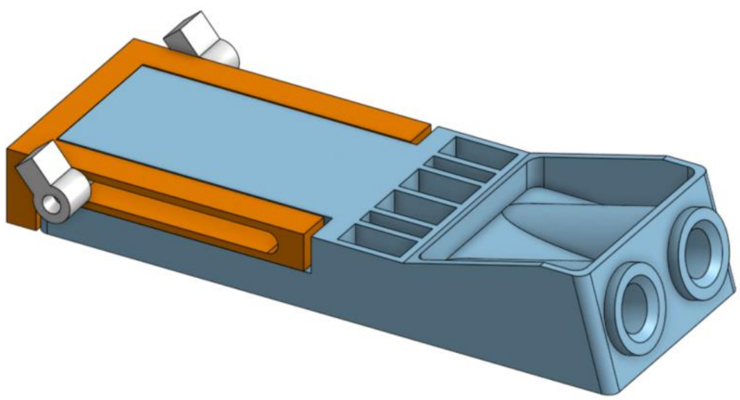
Appendices

Appendix A. Alternative Design Tasks

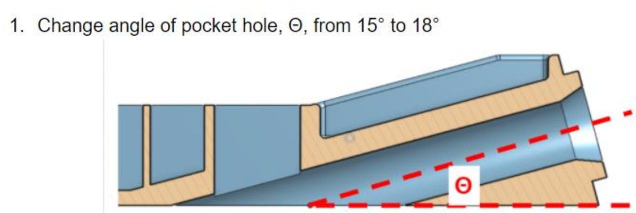
A1. List of Design Change Requirements for Provided Model

A potential option explored in depth is aimed directly at the "*Modification of an existing product/part in CAD"* scenario outlined earlier. A pre-made CAD model would be provided to the participants, along with a list of required design changes similar to what a design engineer might contend with after conducting product testing or receiving customer feedback.

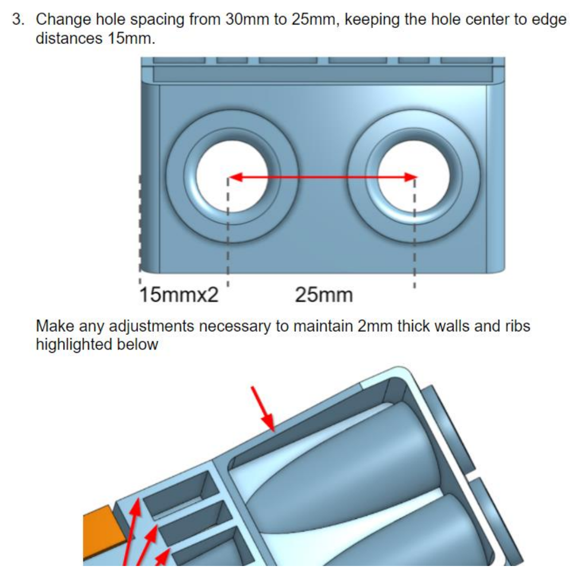
A pocket jig hole jig model was created along with an instructions sheet to be provided to the participants during the experiment:



The instructions sheet includes some context for those who are unfamiliar with pocket hole jigs, then outlines a series of change requests of various difficulty. Some simple changes may only require modifying one sketch or feature:



While others require the participant to modify multiple features to fulfill the change requirements while maintaining the original design intent:



In the end, we decided to not proceed with this task due to the following concerns:

- It was challenging to determine the proper scope for this task. Too simple, the change requests become trivial and do not reveal much insight. On the other hand, if the task was too open ended, we run the risk of being overly ambiguous and using up too much time. Too much variation also makes maintaining scoring consistency a big challenge
- How the pocket hole jig CAD model was created also introduces a confounding variable that is hard to isolate and remove. My particular personal modelling style may align well with some participants but run counter to the preference of others. That could impact people's performance level in a way that would be difficult to predict and account for. One potential solution is to have multiple versions of the same jig model created by following different design guidelines or by different people. That would potentially show the impact of CAD styles' effects on people in a modify task, but would require a much larger number of participants in the study.

A2. Recreate an Item In CAD with a Rendered Virtual Object

The design of this experimental task involves providing participants with a 3D render of a model or an imported model with no feature tree and feature history or a rendered 3D object viewable in a different piece of software, then asking them to remake it in CAD. This would be similar to giving people a physical object along with some calipers and asking them to recreate it in CAD. Since in-person studies were not viable, this would be the digital equivalent.

By having everyone work on modelling the same item, it would be relatively easy to compare their models and their model structures to identify effective modelling strategies. This idea was eventually discarded given the awkwardness and nuisance related to taking measurements virtually repeatedly. The workflow would likely slow down participants significantly, rendering more complex models unsuitable.

A3. Model an Item of Participant's Choosing

Another option is to have participants make a model of something of their choice, with some guidelines on recommended item types and complexity level. Such as "pick an item from your toolbox", or "pick an item you use often for one of your hobbies". While contextual information and familiarity with the product would likely improve people's performance, participants working on different modelling tasks makes comparisons between users difficult and creates a challenge for maintaining consistent modelling task complexity.

A4. Speed CAD

We also considered designing the experimental tasks to mimic speed CAD competitions that are popular among some CAD aficionados. Essentially the tasks would involve multiple of rounds of CAD modelling where the main goal is to model as quickly as possible based on provided drawings. The models generally are not extremely complex, but some of the design details still require considerable amount of CAD competence to complete correctly and quickly. The fastest users typically take between 5 to 15 minutes for each model, depending on the difficulty level. Here is one example of a typical modelling task in one of these competitions:

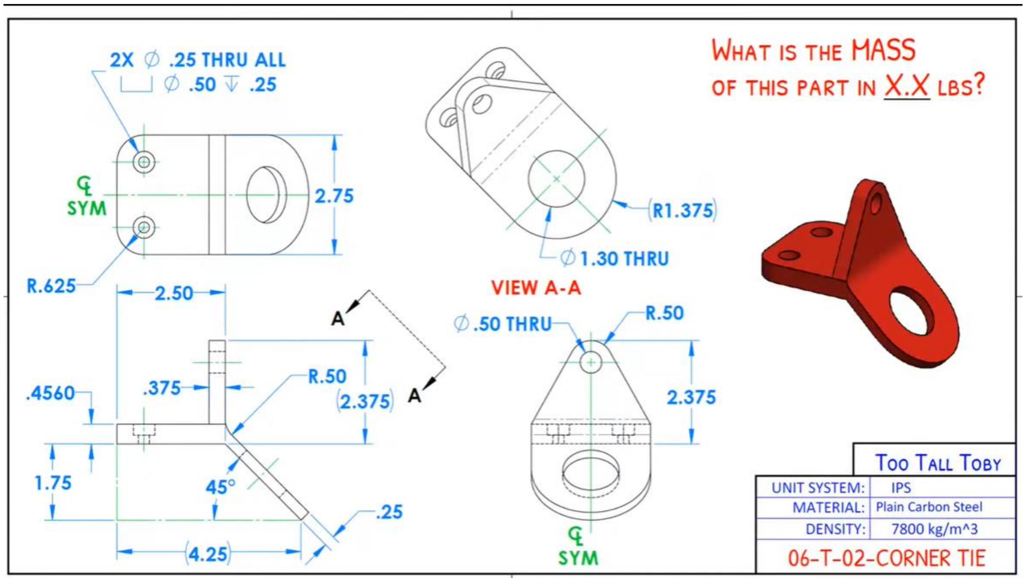


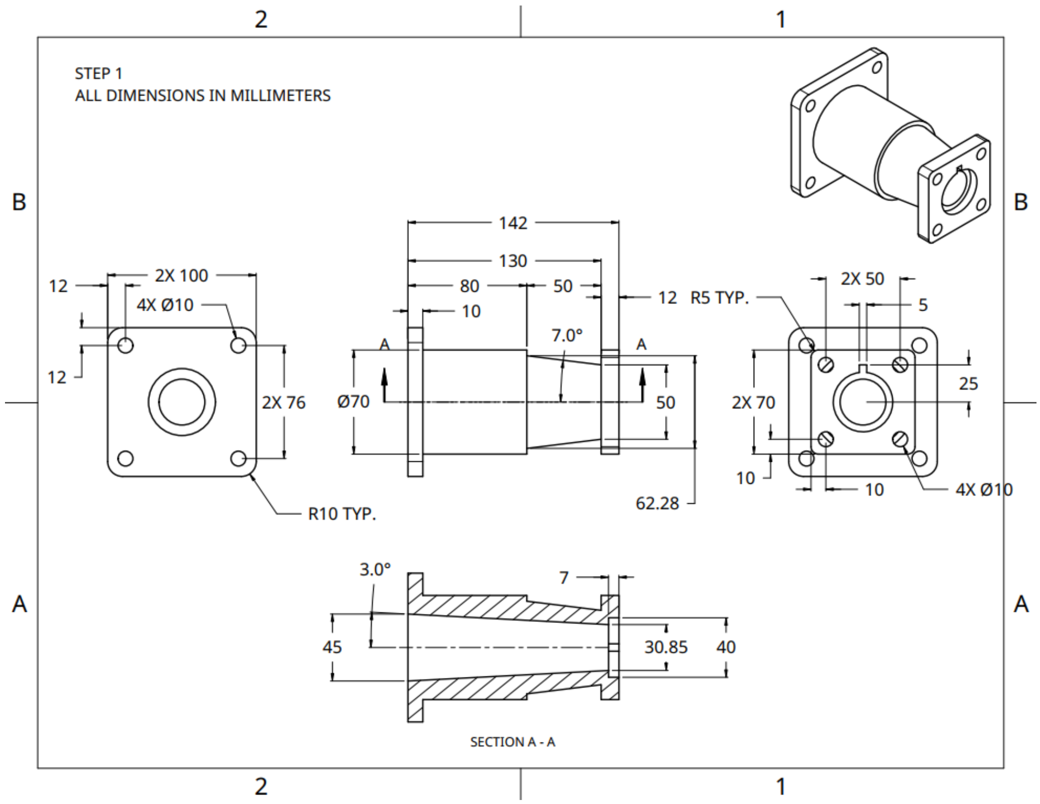
Figure 40 Example Speed CAD Competition Drawing [44]

This type of modelling activity provides a good gauge on a user's overall familiarity with a particular CAD system as well as one's ability to mentally break down the model and determine the optimal sequence of operations that would arrive at the correct final geometry in a short amount of time. Sound modelling approaches and strong fundamentals will likely become evident in a speed CAD competition, potentially helping to highlight efficient modelling techniques. We initially thought having multiple shorter CAD sessions during the study would potentially generate more data, but due to the limitations in the data collection method, this was later found to not be the case.

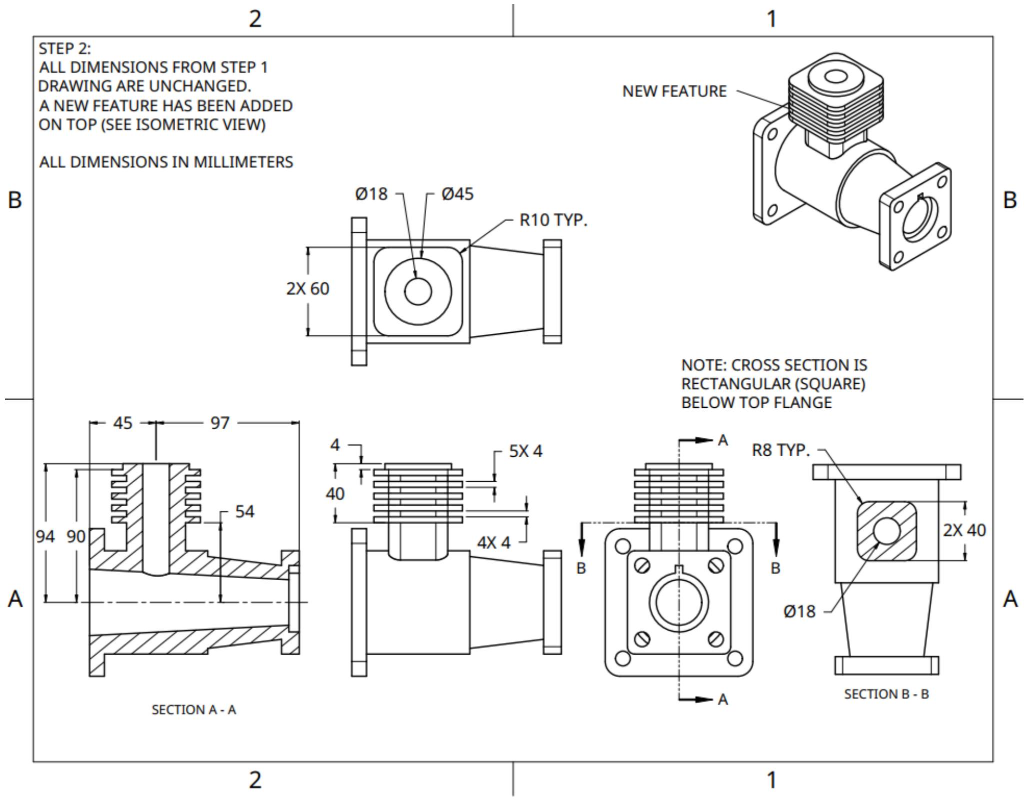
However, there are also a few issues regarding this particular experimental task. Chief among them is the fact that most users don't typically create CAD models under high levels of time pressure. Artificially creating a high-pressure environment would tend to push participants to seek out shortcuts that often run counter to CAD best practices. This effect would likely be even more evident among those less familiar with CAD. Given our goal is to capture people's typical usage of CAD, a speed CAD style experimental task would provide the wrong incentives to participants and skew our results. Another concern is that the experimental task could also unintentionally penalize participants who have less experience reading engineering drawings. Lastly, under time pressure, most participants would unlikely take time to perform any organizational actions, such as renaming features or reorganizing the feature tree, which we know from research as part of an effective CAD model strategy.

Appendix B. Task 1 and 2 Instructions Drawings:

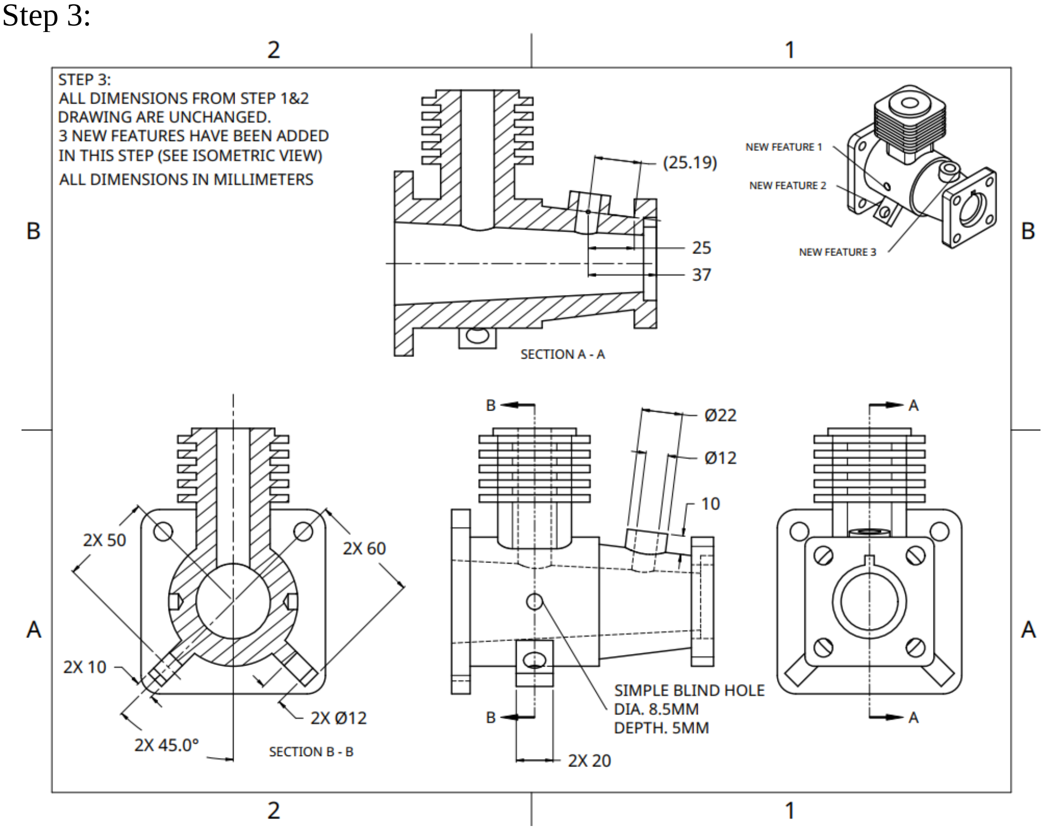
Task 1 Step 1:



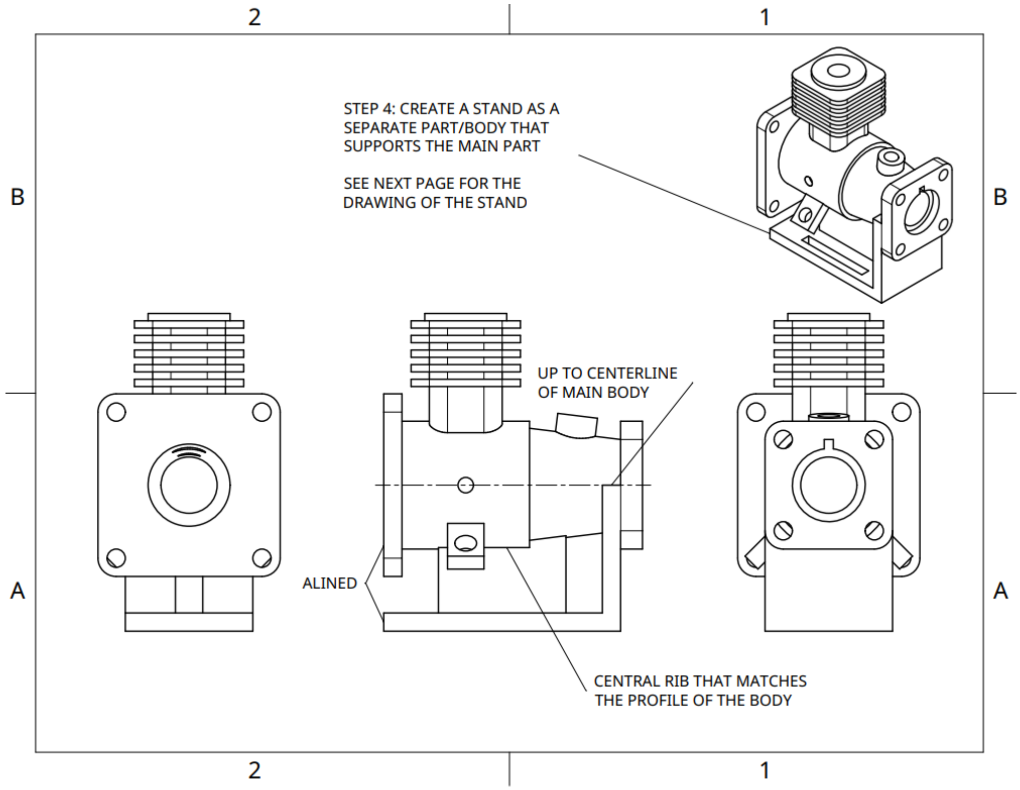
Task 1 Step 2:

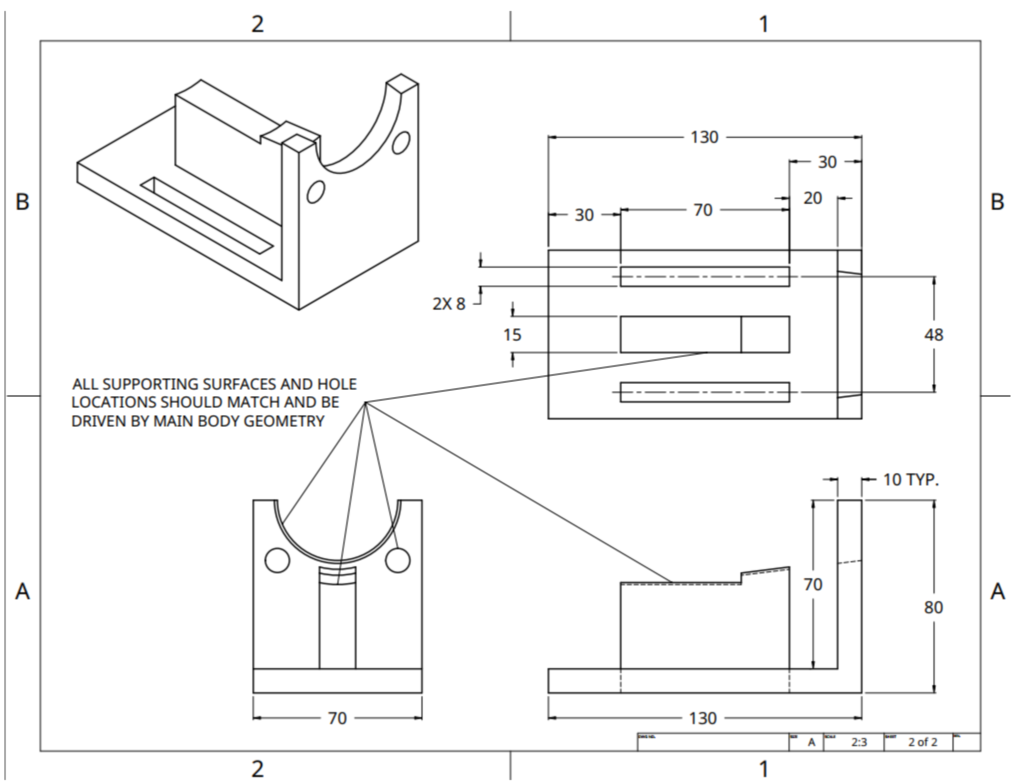


Task 1 Step 3:

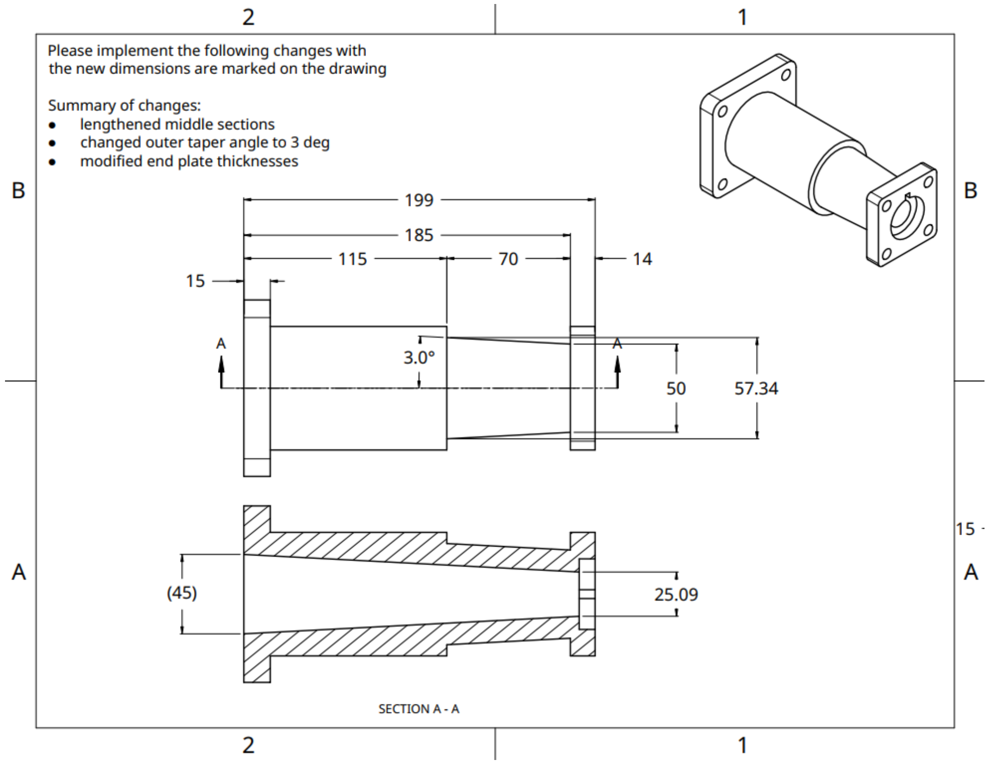


Task 1 Step 4:

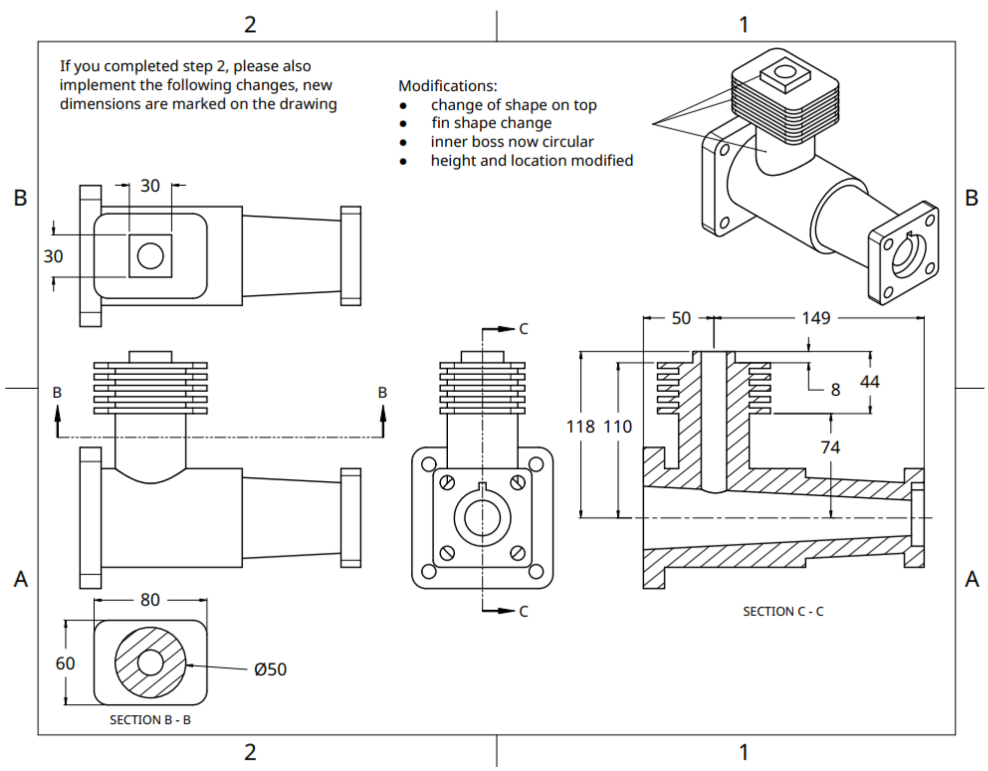

STEP 4: CREATE A STAND AS A SEPARATE PART/BODY THAT SUPPORTS THE MAIN PART
SEE NEXT PAGE FOR THE DRAWING OF THE STAND
UP TO CENTERLINE OF MAIN BODY
ALINED
CENTRAL RIB THAT MATCHES THE PROFILE OF THE BODY
2
1
B
A


130
30
30
70
20
2X 8
15
48
ALL SUPPORTING SURFACES AND HOLE LOCATIONS SHOULD MATCH AND BE DRIVEN BY MAIN BODY GEOMETRY
10 TYP.
70
80
70
130
A
2:3
2 of 2

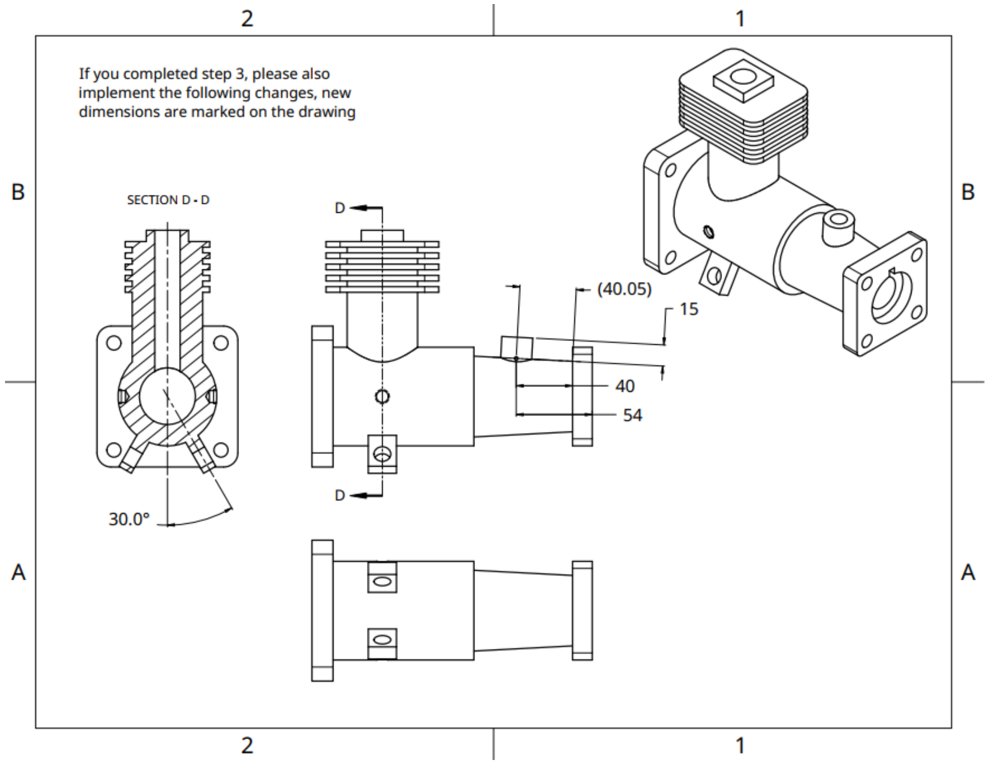
Task 2 Step 1:



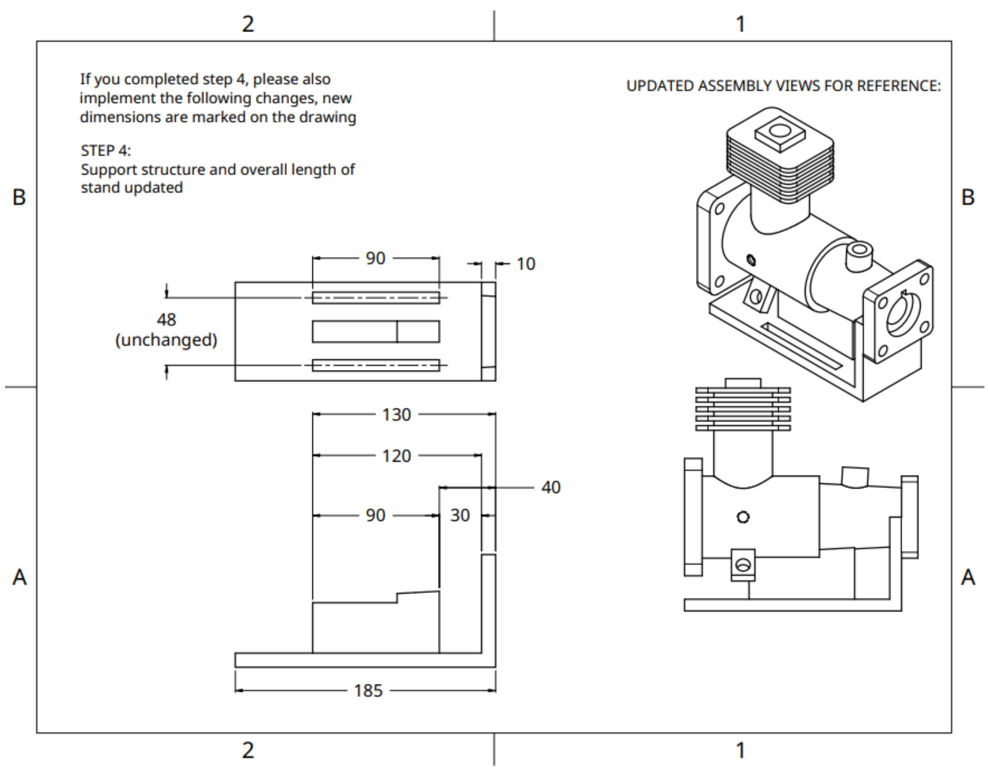
Task 2 Step 2:



Task 2 Step 3:



Task 2 Step 4:



Appendix C. Initial Interest (Sign up) Form

Please provide your First and Last name:
____

Please provide your email:
____

Do you currently use CAD on a regular basis?

- ◯ Yes
- ◯ No

Is Onshape the main solution you use for CAD?

- ◯ Yes
- ◯ No

What level of 3D CAD user would you consider yourself to be? Please select the level that closest represents your CAD experience level.

Novice: I understand the basics of CAD, have made a few simple parts and followed some CAD tutorials. I have used CAD for course labs/personal projects/team projects

Intermediate: I am comfortable making medium to high complexity parts that include multiple sketches, datums, and features. I have used CAD for personal and/or team projects and made meaningful contributions to the models

Advanced: I have extensive experience using CAD in a professional setting or teaching CAD to students, with a good mastery of CAD principles and regularly work with large CAD models with complex geometries/assemblies and large feature-counts

- ◯ Novice
- ◯ Intermediate
- ◯ Advanced

Are you currently an Onshape/PTC employee?

- ○ Yes
- ○ No

Are you over the age of 18?

- ○ Yes
- ○ No

Appendix D. Pre-study Survey

Ready Lab CAD Study Onshape Pre-Study Questionnaire

Your Name (First & Last)

____

What is your age?

____

What is your gender?

- ◯ Male
- ◯ Female
- ◯ Prefer not to disclose
- ◯ Other ____

What is your ethnic background?

- ◯ Asian
- ◯ Arabic
- ◯ Black / African American
- ◯ Indigenous
- ◯ Latin American
- ◯ White / Caucasian
- ◯ Prefer not to disclose
- ◯ Other: ____

Where are you located?

- North America/Central America
- South America
- Europe
- Africa
- Asia
- Australia
- Caribbean Islands
- Pacific Islands
- Prefer not to disclose
- Other: ______ ____

What is the highest degree or level of school you have completed?

- Less than a high school diploma
- High school degree or equivalent (e.g. GED)
- Some college, no degree
- Associate degree (e.g. AA, AS)
- Bachelor's degree (e.g. BA, BS)
- Master's degree (e.g. MA, MS, MEd)
- Doctorate or professional degree (e.g. MD, DDS, PhD)

What is your current employment status?

- ◯ Employed full time in industry
- ◯ Student
- ◯ Co-op / Internship
- ◯ Retired
- ◯ Other ____

Display This Question:

If What is your current employment status? = Student

Or What is your current employment status? = Co-op / Internship

What year of university have you just completed?

- ◯ Have not started university yet
- ◯ 1
- ◯ 2
- ◯ 3
- ◯ 4
- ◯ 5
- ◯ I am a Masters/PhD student. Year: ____

Display This Question:

If What is your current employment status? = Student

Or What is your current employment status? = Co-op / Internship

Which educational institution are you currently enrolled in?

____

Display This Question:

If What is your current employment status? = Student

Or What is your current employment status? = Co-op / Internship

What is your major?

____

End of Block: Demographics

Start of Block: Professionals & Intern/co-ops

Display This Question:

If What is your current employment status? = Employed full time in industry

Or What is your current employment status? = Co-op / Internship

What industry do you currently work in?
(Some examples include: consumer electronics, automotive, medical, aerospace)

____

Display This Question:

If What is your current employment status? = Employed full time in industry

Or What is your current employment status? = Co-op / Internship

What is your current role at your place of employment?
(Some examples include: Mechanical engineer, Engineering Manager, Product designer, CAD drafter, FEA analyst, etc.)

____

Display This Question:

If What is your current employment status? = Employed full time in industry

Or What is your current employment status? = Co-op / Internship

How many years have you been at your current company?

____

Display This Question:

If What is your current employment status? = Employed full time in industry

Or What is your current employment status? = Co-op / Internship

Do you do engineering design work?

◯ Yes

◯ No

Display This Question:

If What is your current employment status? = Employed full time in industry

Or What is your current employment status? = Co-op / Internship

What type of design work do you spend the most time on?
(Some examples include: detail part/component-level design, assembly design, integration, FEA/simulation, etc.)

____

What is the main CAD package used by your company?

◯ Onshape

◯ NX

◯ CATIA

◯ SolidWorks

◯ Solid Edge

◯ PTC Creo (ProE)

◯ Fusion360

◯ AutoCAD

◯ Other ____

End of Block: Professionals & Intern/co-ops

Start of Block: CAD Experience

What level of 3D CAD user would you consider yourself to be? Please select the level that closest represents your CAD experience level. Novice: I understand the basics of CAD, have made a few simple parts and followed some CAD tutorials. I have used CAD for course labs/personal projects/team projects

Intermediate: I am comfortable making medium to high complexity parts that include multiple sketches, datums, and features. I have used CAD for personal and/or team projects and made meaningful contributions to the models

Advanced: I have extensive experience using CAD in a professional setting or teaching CAD to students, with a good mastery of CAD principles and regularly work with large CAD models with complex geometries/assemblies and large feature-counts

- ○ Beginner
- ○ Intermediate
- ○ Expert/Advanced

CAD software solution(s) are you most familiar with?

- ☐ Onshape
- ☐ NX
- ☐ CATIA
- ☐ SolidWorks
- ☐ Solid Edge
- ☐ PTC Creo (ProE)
- ☐ Fusion360
- ☐ AutoCAD
- ☐ Other ____

How much experience do you have in CAD in total across, all CAD programs?
(periods of time where you consistently used CAD, could be for professional work, school projects, clubs, or hobbies)
You can either answer in years & months, or total hours, whichever is easier to tally

- ○ Years, Months (ex: 5,2 for 5 years, 2 months) ____
- ○ OR Total Number of Hours ____

How much of the above was spent on Onshape specifically?
You can either answer in years & months, or total hours, whichever is easier to tally

◯ Years, Months (ex: 5,2 for 5 years, 2 months) ____

◯ OR Total Number of Hours ____

Have you taken any CAD certification exams before? (Such as: SolidWorks CSWA/CSWP, Certified Onshape Professional exam, or similar)

◯ Yes (please list the certifications you received) ____

◯ No

Have you ever received formal CAD training?

◯ Yes

◯ No

Display This Question:

If Have you ever received formal CAD training? = Yes

Please briefly describe the training. What type of training was it? How long was the program? What topics were covered?

____
____
____
____
____

End of Block: CAD Experience

Start of Block: Consent

Lastly, I agree to put away my phone and pay full attention for the entire duration of the study

◯ Yes

◯ No

End of Block: Consent

Start of Block: Students

Appendix E. Experiment Interview Questions

Task 1

- How did it go? Did you run into any issues?
- Can you describe your general strategy for creating CAD models?
- What do you first start with? How do you define your base/first feature?
- How did you decide where to place the origin in your part? Was that a conscious decision?
- Did you have to make any trade-offs between speed and quality?
- Did you model in a way that makes it easier to edit down the road? If so, how?
- Did you make any other trade offs while modeling that you normally wouldn’t have?
- Could you explain your datum scheme and how you chose to dimension your model?
- What are some strategies you have developed over time to speed up your CAD modeling, or improve the robustness of your models?
- Were you favoring speed, modifiability, flexibility, accuracy while you were designing?
- If you have switched from another CAD system to Onshape, have you developed different workflows or techniques? What were they and why were they necessary?

Task 2:

- Did you run into any problems while editing your model?
- What are some aspects of your model that helped make editing it easier?
- If you were to go back and redo the model, is there something you would have done differently? What and why?
- Did you find going back and editing your model made you realize any improvements or differences in approach you hadn’t noticed earlier?

Appendix F. Full List of Audit Trail Actions

Table 8 Audit Trail Actions in Description and User Action Mapping

#	User Action	Sequence of Actions	Onshape Audit Trail Description
P1	Add a new sketch	Start creating	Add part studio feature
		Finish creating and commit	Commit add or edit of part studio feature Insert feature : Sketch 1 Add or modify a sketch
P2	Add a new part studio feature	Start creating	Add part studio feature
		Finish creating and commit	Insert feature : Extrude 1 Commit add or edit of part studio feature
P3	Edit a part studio feature	Start editing	Start edit of part studio feature
		Finish editing and commit	Commit add or edit of part studio feature Edit : Extrude 1
P4	Edit a sketch	Start editing	Start edit of part studio feature
		Finish editing and commit	Add or modify a sketch
P5	Delete a sketch/part studio feature	Deleting a feature	Delete : Extrude 1 Delete part studio feature
		Deleting multiple features	Delete : 3 features Delete part studio feature Delete part studio feature Delete part studio feature
P6	Suppress a part studio feature		Suppress : Extrude 1
P7	Rename a sketch/part studio feature		Rename : Master Sketch
P8	Cancel editing a sketch/ feature	Start editing the feature	Start edit of part studio feature
		Cancel the operation	Cancel Operation
P9	Start creating a new sketch/ feature without committing the one being edited	Start creating a sketch	Add part studio feature
		Start an extrusion without first committing the sketch being edited	Add part studio feature Commit add or edit of part studio feature Insert feature : Sketch 1 Add or modify a sketch
P10	Show/Hide a sketch	Hide a sketch	Hide Sketch 1
		Show a sketch	Show Sketch 1
P11	Roll back the rollback bar in the feature tree		Move : Rollback bar
P12	Copy and paste a sketch	Copy a sketch	No Record
		Paste a sketch on a feature (e.g., a face of a block)	Add part studio feature Copy paste sketch Paste : sketch

		Paste a sketch in another sketch	Copy paste sketch
P13	Assign material to a part		Assign material : Part 1
P14	Change appearance of part (e.g., colour)		Change part appearance : Part 1
P15	Suppress/ Unsuppress feature(s)	Suppress a feature	Suppress : Extrude 1
		Unsuppress a feature	Unsuppress : Extrude 1
		Suppressing multiple features at the same time	Suppress : 3 features
P16	Add a face appearance to a part	Start adding the face appearance	Add sub-part property
		Commit add	Add : Face appearance 1 Commit sub-part property edit
P17	Change the face appearance of a part	Start editing the face appearance	Edit sub-part property