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What Sets Proficient and Expert Users Apart? Results of a Computer-Aided Design Experiment

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As computer-aided design (CAD) tools have become an essential aspect of modern mechanical engineering design, the demand for CAD experts has increased significantly. The development from novice, to proficient, to expert user is of particular interest to the industrial and academic design communities. Yet little is known about the development of modeling choices, strategies, and patterns that characterize expert CAD skills; much of the past work that reports user action data is based on student or novice data. We compared the CAD modeling process across nine proficient and ten expert designers as they were tested to complete the same design task. Under identical conditions—the same time constraints in the same CAD platform and with the same task—the expert users were able to complete a larger proportion of the task with higher dimensional accuracy. While the experts were able to dissect and retrieve geometries from manufacturing drawings more efficiently than proficient users, they were also able to plan a modeling strategy that required less effort and revisions. With our experimental findings, we identify the demand for procedural knowledge-building for young engineers, with the ultimate goal of more effectively developing experts in engineering design with CAD.
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1 Introduction

Computer-aided design (CAD) has become an indispensable tool in the modern field of mechanical engineering design and manufacturing. The fundamental role of CAD is to create computational representations for manufacturing specifications of products through 2D drawings and 3D models [1]. The use of CAD supports engineering work in design, analysis, and communication, which eventually leads to better engineering task performance [2]. CAD has been increasingly important given the growth of new technologies such as augmented and virtual reality [3], mechanical simulations [4], and additive manufacturing [5]. With the availability of big data, as increasingly shared online, and accessible through modern cloud platforms, CAD has also been an effective tool for researchers to understand modeling processes and design thinking [6–8]. These advancements—more data and improved interfacing—further support the development of related artificial intelligence (AI) technologies in CAD [9–11]. While the popularity and importance of CAD continue to grow, the existence of CAD has long been embedded in almost all stages of the product development process [12].

Reflecting the growing demand for expert CAD designers in industry, modern engineering education includes CAD instruction, with the ultimate aim of teaching engineering design, analysis, and collaboration [13]. A basic engineering education from university programs and entry-level work experience likely enables new graduates to construct models with medium to high complexity in CAD, but few are yet CAD experts. As in any other field, it takes time and deliberate practice to become an expert through gained experience [14–16]. Yet a major gap persists in our knowledge of modeling expertise, and correspondingly CAD expertise, as raised by Cross in 2004: "How is the transition made from novice to expert?" [17].

Two engineers may use different modeling approaches to reach geometrically identical final products with modern CAD software. They may make different modeling choices, in different orders, or develop patterns in the features they choose. The variability in the modeling process is widely observed among different designers in CAD [18]. Meanwhile, some approaches are certainly more efficient than others, some approaches better capture the design intent of the model [19], and some approaches result in more robust and flexible models to be reused for future design iterations [18,20]. While novice designers do not necessarily need to worry about modeling efficiency and flexibility in their early learning process, they tend to rely on trial and error when approaching a modeling task [21]. This trial-and-error approach is not particularly

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interesting to study from an analytics perspective—the data can be noisy, and they are difficult to characterize consistent patterns, which we would expect to see in the analytic footprints of more experienced designers.

Indeed, few studies characterize the modeling process of expert CAD designers, and many studies of design behaviors have been based on novices, and usually students, due to the challenges in recruiting experts [17]. In the broader field of design, some studies exist of either experts with extensive professional engineering experience or novices that are new to the field (students in most cases), where comparisons are sometimes made between these two groups [21–24]. The same is also true for CAD research specifically; while CAD has been an important part of the engineering curriculum for many years, most design and modeling research in CAD is based on student (novice) data and largely focuses on educational settings [25–31]. The CAD research based on industry CAD experts is predominantly conducted at small scales [32,33]. Nevertheless, little work exists to characterize expertise levels apart from the binary of novice and expert; our study focuses on an intermediate level of expertise, which we call "proficient." We are motivated to compare proficient, instead of novice, and expert designers because, as we will later describe, we expect that proficient users and expert users have developed sufficient declarative knowledge such that the actions that we witness are meaningful intentions versus experimentation or learning. Therefore, we tap into the users' procedural knowledge, which has been described as key to CAD expertise. While we cannot expect someone to transition from a novice to an expert at once, better understanding the expertise of a proficient user allows us to identify the most prominent characteristics of, and hence the gap from becoming, an expert in CAD.

In this study, we aim to investigate the difference in CAD modeling between design experts and designers who are proficient, but not yet expert. Following the industry-standard approach that is used to test the CAD skills of individuals, as how most CAD software providers test their users when issuing certificates of mastery of the tool [34–36], we designed a four-step modeling task that asks the participants to re-create a solid model in CAD given its manufacturing drawings. Under identical time constraints, we evaluated the completeness and correctness of the resulting models from the two groups of participants, where we found that the self-identified experts were indeed able to complete a larger portion of the task with higher dimensional accuracy. Closely studying the modeling actions of every participant, we compared the action counts, the time spent on each action type, and the transitions between consecutive actions of the two groups of participants. Analysis showed that the difference in modeling performance, as measured by both task completeness and correctness, between experts and non-experts was observed to be impacted by modeling efficiency in sketch creation and model revision. Further, experts also showed more strategic referrals to drawings during the CAD modeling process. Finally, we discussed how these findings may inform future modeling behaviors with CAD and the field of engineering education.

2 Background

2.1 Declarative and Procedural Knowledge in Computer-Aided Design. Cognitive psychologists categorize knowledge into two types: declarative and procedural (also known as strategic) knowledge [37]. Declarative knowledge focuses on the specific commands and procedures used to achieve a goal, while procedural knowledge considers the alternate methods by which the same goal may be achieved and the process by which a choice may be made [38]. In the specific context of CAD, declarative knowledge consists of the mastery of commands that a designer carries out within the software to use the modeling features, and procedural knowledge consists of the higher-level strategies that the designers use to carry out the series of commands [27]. Meanwhile, both types of knowledge in CAD can be highly cognitive and hard to be quantified for evaluation [39]. To model effectively and efficiently in CAD, the possession of both types of knowledge is critical. But logically, a designer would need to first develop a solid foundation of declarative knowledge in CAD before being able to develop procedural knowledge through modeling experience.

Declarative knowledge is typically the only form of knowledge taught in short-term CAD training courses and written in technical product manuals, at least partly because from the CAD software development standpoint, effectively explaining and improving the functions of the features (i.e., the declarative knowledge of CAD) are the immediate focus of CAD service providers. These effects have been demonstrated among novice designers, for example, Peng et al. found that novice students do not naturally consider factors such as model robustness and flexibility for reuse and modifications in CAD unless otherwise incentivized to do so [25]. Thus, designers learn high-level modeling strategies (i.e., procedural knowledge) either through some form of long-term education or extensive experience in the industry. Unfortunately, the didactic approach has long been the dominant pedagogy for learning in both education and industry, and such initial teaching plus experience does not necessarily lead to the development of expertise [40]. The lack of improvements via didactic approaches on students' analytical, strategic, and visuospatial abilities eventually led to deficiencies in digital modeling abilities [41].

Via years of research in product design and solid modeling in CAD, researchers and industry experts have developed various best practices for CAD modeling, an important part of the procedural knowledge in CAD. While different modeling strategies have different foci, one over-arching best practice is to build models that are more parametrically stable with the design intent clearly conveyed for other designers to understand [19,20,28,42,43]. In such a way, the CAD models can be maintained more sustainably for long-term product development. Based on findings from past research, the expertise of procedural knowledge is often the main differentiation between expert designers and students in CAD [44]. Even though the mastery of different CAD systems likely requires different declarative knowledge, the procedural knowledge developed via the use of any CAD system was found to be highly transferrable and advantageous for expert designers [27]. When designing in CAD, Ahmed et al. found that experienced designers were more likely to use particular design strategies, which novices were unaware of, instead mainly relying on trial and error [21]. To enable CAD training that emphasizes the acquisition of procedural knowledge, existing proposals often focus on the application of cognitive apprenticeship, where the trainees can learn from experts about both the dissection of the problem and the modeling process at the metacognitive level [45,46].

As the literature suggests, the expertise of procedural knowledge has been described as the main gap that a novice engineer or designer needs to develop through their career to become an expert. In this study—as a main differentiator from the existing CAD analytics literature which examines novice CAD users—we recruited both experts and proficient CAD users in this specific software platform, such that they had already developed sufficient declarative knowledge of CAD. In this way, our study can more precisely identify differences in observed actions, which we expect to be driven by differences in procedural knowledge.

2.2 Studies of User Actions in Computer-Aided Design. Traditional research on engineering design processes mainly relies on interviews, surveys, and audio and video recordings [23,32,47]. While these analysis methods provide high resolution and flexibility, they typically require time- and labor-consuming qualitative analysis that is prone to be subjective, whereas methods that enable computer-based data collection and automated analysis are sorely needed [48]. In recent years, researchers have started to utilize user analytics that records both geometric data of the features and user actions committed in CAD [7]. This emerging research method does not only provide fine-grained data on modeling actions in CAD for scalable data-driven design analysis, but it also enables data collection that is non-obtrusive to the research subjects during the design process [6,49,50].

With a large amount of analytic data being logged for a modeling process in CAD, the most fundamental analysis that can be performed is to count the number and time spent on actions aggregately. Due to the large variety of actions that are usually tracked in a CAD platform, user analytic data are often first categorized into a smaller set of meaningful categories that are both manageable for research interpretation and designed to answer the research questions that a study aims to solve [6,50,51]. Then, analyses can be performed by comparing the number of actions in different categories [50–52], the proportion of different action categories [50,51], and the densities (or frequencies) of actions of specific types between users [29,53]. Further, customized ratios that combine and compare multiple action categories can be used as effective metrics of specific modeling behaviors that are of interest in the study [29,52,53].

While aggregate measures of user analytics enable efficient analyses and comparisons between designers in CAD, the analytic data themselves are time-based in nature. As user analytics typically records modeling actions with timestamps of occurrence, researchers can theoretically rebuild the entire design process based on the collected data logs in chronological order. For small-scale experiments, qualitative coding of time segments [23], and even simply plotting out the complete data log over time [18,52,53], can effectively allow visual comparisons between multiple time-series sequences to identify differences in the design process. For datasets of larger scale, some researchers have focused on the transition between actions. Markov Chains and hidden Markov models (HMMs) are often used to find process heuristics from designer data for best design practices in CAD [6,51,54,55]. Studying the transitions between actions often assumes all transitions to be independent of time, ignoring the difference in behaviors in different stages of the design process. With a large quantity of time-series design process data, machine learning technique can be applied such as deep learning neural networks [11,56,57], clustering algorithms [6,33], and Bayesian network models [58].

In this study, we analyzed the modeling process primarily based on user analytic data (essentially all mouse clicks committed by the users) that were collected non-intrusively by the CAD platform in the backend. As we applied metrics with aggregate counts of different types of actions to compare the full modeling process between participants, we also examined the transition between modeling actions using the hidden Markov models. We expect the utilization of both data analysis approaches would help us to dissect the difference between proficient and expert designers in CAD with both high-level and detailed comparisons.

3 Method

For this experiment, we designed a 35 min-long modeling task, where participants were asked to rebuild a model in CAD given a corresponding set of manufacturing drawings. Here we aim to collect CAD modeling actions from skilled designers in a natural and non-intrusive manner. The practice of rebuilding physical models in CAD has been a widely adopted method for CAD instruction as well as a technique for designers to improve their CAD skills by working on a well-defined and close-ended modeling problem. In fact, nearly all commercially available CAD software platforms nowadays adopt a similar task when testing users' ability to master the features in their software, where certificates are awarded to those who can accurately re-create the given model [34–36]. This type of task allowed us to compare performance and approach across participants in a way that is not possible with an open-ended task where final designs may be vastly different. While CAD modeling in and of itself is an important skill for detailed design, the closed-ended nature of the task is not necessarily generalizable to open-ended design more broadly; corresponding limitations resulting from our choice of task are further discussed in Sec. 5.3.

Our study participants were asked to self-identify as either an expert- or a proficient-level CAD designer from a three-level scale developed to describe background CAD skills and experience (exact descriptions are introduced in the following sections). After the experiment, we first evaluated the completeness and correctness of the resulting CAD models of the two groups of participants in this modeling task. With all modeling actions collected non-obtrusively during the modeling process, we were then also able to compare the difference in the modeling process between designers with different levels of CAD expertise. This study was reviewed and accepted by our institutional ethics review board.

3.1 Experiment Settings. As shown in Fig. 1, the full experiment session lasted 90 min, conducted in a fully virtual setting through Zoom. The experiment first started with an introductory presentation, where the overall experiment flow and general instructions were explained to the participant, along with the context for the study. Specifically, participants were repeatedly told to not rush through the tasks and maintain high standards, and follow their typical CAD workflow. For both CAD tasks, participants received one verbal cue near reaching the end of the allowed time for each of the two tasks (10 min for Task 1 and 5 min for Task 2). Meanwhile, no additional instructions were given by the researchers once the tasks started. After the introduction, the participants were asked to share their screens throughout the experiment for the researchers to record their actions within the CAD interface. Meanwhile, all participants were asked to use one computer screen only, such that it was consistent among participants.

In the first task (Task 1) participants were asked to create a CAD model from scratch based on the given manufacturing drawings (more details explained in Sec. 3.3). This paper focuses solely on this task, and it is referred to as the *modeling task* hereafter. In Task 2, participants were asked to modify their CAD model from Task 1. Task 2 is excluded from this paper because it was found to be too easy and could not differentiate participant performance. Effective comparisons between participants were also not feasible for Task 2 as modifications on geometries created in latter steps of Task 1 could not be performed for participants who did not finish those steps in Task 1. Short interviews were also conducted at the end of each task to allow participants to explain their modeling strategy.

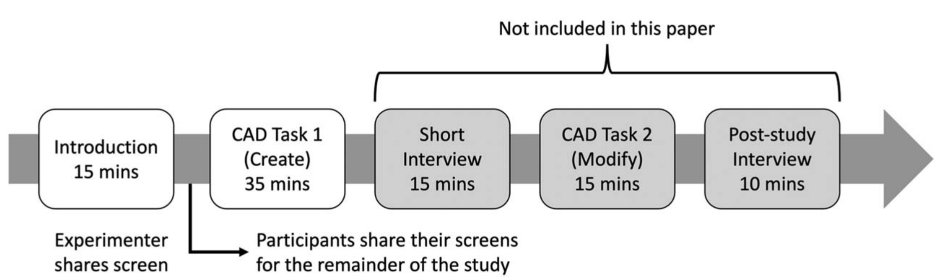

Fig. 1 The flow of the experiment

All experiment tasks were delivered and completed in ONSHAPE, a cloud-based CAD platform. Modeling in ONSHAPE is very similar to any other commercially available mechanical CAD software. However, all files are accessed and hosted through a web browser. In ONSHAPE, a document acts as a container that holds all related files (e.g., drawings in PDF format) and CAD designs (e.g., parts and assemblies) related to a project. Meanwhile, the researchers were able to manage all files in the lab's ONSHAPE Enterprise account. Before the experiment, each participant was given access to an ONSHAPE account created by the researchers, and they were allowed to personalize interface settings (e.g., keyboard shortcuts) to match their preferences. Meanwhile, an ONSHAPE document was created for every participant with all detailed experiment instructions provided within the document. Participants were only given access permissions to the documents when the task started, and the access was then revoked right after the task ended.

As a user model in ONSHAPE, the platform also automatically logs all actions the user commits. Essentially, every click the user makes will be recorded non-intrusively in the backend (e.g., "Tab Step 1.pdf of type PARTSTUDIO opened by [participant]," "Insert feature: Sketch 1," "Edit: Extrude 1"). After the experiments, the researchers were able to export all user actions in the form of an audit trail, where all actions can be retrieved sequentially with timestamps to algorithmically rebuild the modeling process. Especially, for the use of every CAD feature in ONSHAPE, the start and end (completion) times of the feature are recorded.

3.2 Participants. We recruited and studied participants who were either proficient or expert CAD users. All CAD modeling tasks were performed in ONSHAPE; since we did not want to study the effects of learning a new software tool, we targeted participants with experience designing in ONSHAPE specifically. Thus, research participant recruitment messages were sent to university students through instructors of specific CAD design courses, industry CAD users through PTC Inc., Boston, MA (the parent company of ONSHAPE), and CAD hobbyists through the public ONSHAPE forum. Participants were compensated at a rate of $15/h, except seven PTC employees (four experts and three proficient users, as defined below), who participated voluntarily and received no compensation at the request of PTC.

All participants were required to have used CAD software of any brand for at least 12 months consistently, where more than 6 months of previous CAD experience must be ONSHAPE specific. Upon the expression of interest in participation, participants were also asked to self-identify their CAD ability level, where three choices were given as follows:

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

Meanwhile, only individuals who self-identified to be either an expert- or an intermediate-level CAD user were considered for invitation. Of the 90 individuals who expressed interest in participating in this experiment, 40 were invited to participate, and 19 individuals (17 men and 2 women) eventually participated in the study. In this paper, participants who selected the "intermediate" option are referred to be *proficient* CAD designers. By definition of their prestudy survey response, they have sufficient CAD skills to comfortably model complex parts but have yet to develop their expertise through professional industry experience.

Based on their self-identified CAD experience levels, all participants were divided into one of the two experience groups, proficient ($n = 9$) and expert ($n = 10$). Meanwhile, all participants were also asked to provide a quantitative estimate of their usage experience, either in terms of hours (e.g., 600 usage hours) or years and months (e.g., 4 years and 3 months). As shown in Fig. 2, experts self-reported generally a greater amount of CAD usage experience

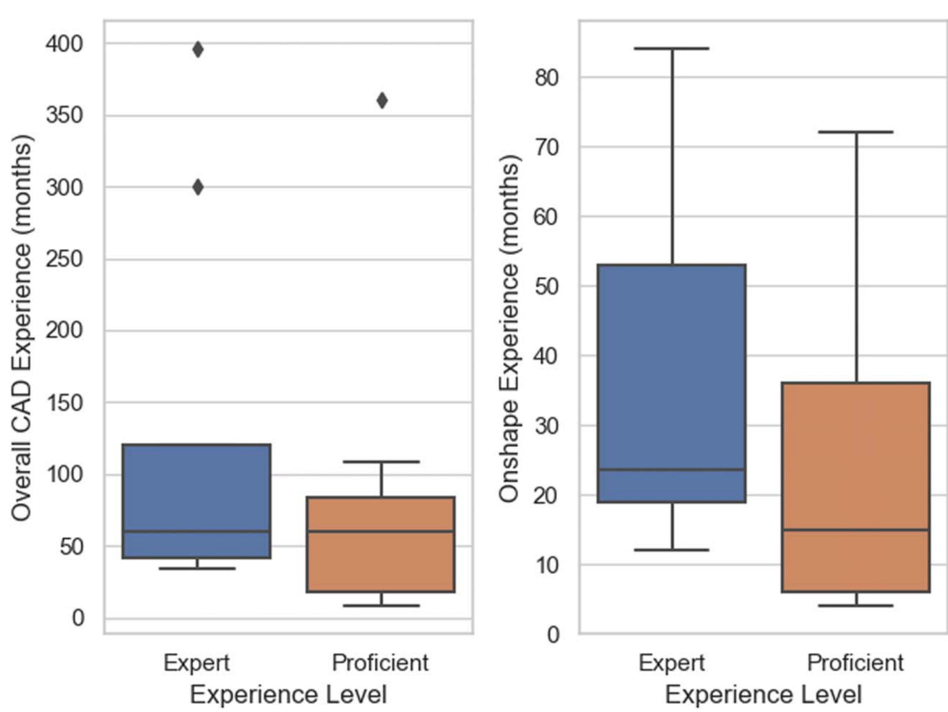

Fig. 2 Self-identified CAD experience of participants in months. The boxes show the quartiles of the dataset, and the whiskers extend to the rest of the distribution. Outliers that lie beyond 1.5 times the interquartile range are marked as points.

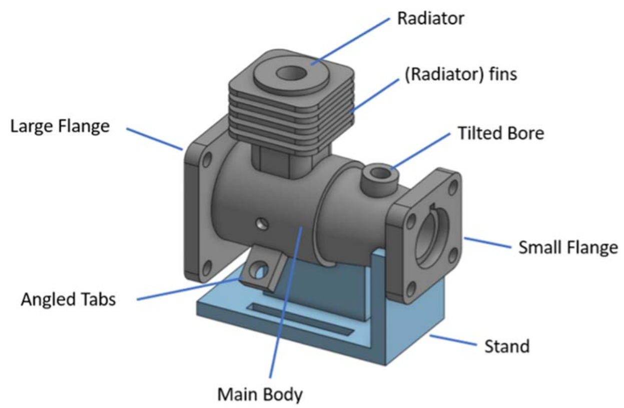

Fig. 3 The final model of the modeling task with major features labeled, for reference

than the proficient group, both across all CAD programs ($\mu_{\text{expert}} = 10$ and $\mu_{\text{proficient}} = 7$ years equivalently) and in ONSHAPE specifically ($\mu_{\text{expert}} = 2.9$ and $\mu_{\text{proficient}} = 2.2$ years equivalently).

3.3 The Modeling Task. The modeling task required the participants to rebuild a CAD model of the reference model shown in Fig. 3. The task was separated into four sequential steps, where the completion of each step requires a roughly equal amount of work, and each step adds new features to the existing model in a progressive manner. The CAD models that the participants were expected to produce by the completion of each step in the modeling task are shown in Fig. 4. As the participants were given access to their ONSHAPE document, the detailed manufacturing drawings with dimensions for each step were already stored in separate PDF files within the document, as shown in Appendix A.

3.4 Performance Evaluation. Although the modeling task was scheduled to be 35 min, we expected the time to complete the full task would be longer. We aimed to place a higher value on the modeling process itself instead of conducting a simple binary evaluation of whether a participant was able to re-create the model with identical dimensions.

To score the participants' models, the same manufacturing drawings were re-labeled with the minimum number of dimensions that can fully define the geometries (60 total). If all labeled geometries of a participant's model match the dimensions in the drawings, the model is deemed geometrically accurate. The version of the drawings that were used for grading is shown in Appendix B.

We measured both the *completeness* and the *correctness* of the participants' model as the evaluation of their performance. Of the 60 total dimensions that fully define the model, assume a participant attempted to build a model that would satisfy $n_{\text{attempted}}$ dimensions and got n_{correct} dimensions matching the correct dimensions, as outlined in the provided drawings, we define

$$\text{Completeness} = \frac{n_{\text{attempted}}}{60}$$

$$\text{Correctness} = \frac{n_{\text{correct}}}{n_{\text{attempted}}}$$

3.5 Analysis Methods. With the participants' modeling process recorded in the form of an audit trail of actions in CAD, we analyzed both the *time spent* on actions and the *transition* between actions. To measure a user's time spent on modeling actions, all action types can first be categorized into a selection of meaningful categories, as outlined in the framework proposed in Ref. [50]. Adapting a metric developed and used in previous works [50,52], we used the *creation/revision time ratio* to measure how well a participant was able to rebuild the CAD model based on the manufacturing drawings with minimum revisions of the features. Essentially, the ratio compares the aggregate time that a user spent on actions that are related to creating new features to the time spent on actions that revise existing features in the model, where a higher ratio indicates fewer revisions.

While comparing aggregate metrics provides a high-level view of participants' modeling processes, time-based patterns must be explored with alternative techniques. Specifically, we aimed to explore process heuristics from the experts that are different from the proficient group. When analyzing the transition between modeling actions, we used an HMM to represent the modeling process of the participants. When training an HMM model, we treat the system of interest (i.e., the modeling process) as having a discrete number of *hidden states* that cannot be directly observed, where each hidden state has a probability distribution associated with a set of possible *emissions* (i.e., the recorded modeling actions). Modeling the entire system as a stochastic process with the HMM, we can study the *transitions* between the hidden states and the relationships between emissions and hidden states [59]. In the field of engineering design specifically, McComb et al. previously showed the effectiveness of using an HMM to describe design processes and discover procedural differences between high- and low-performing designers [55].

4 Results

4.1 General Task Performance. As introduced in Sec. 3.4, we evaluated performance as both the completeness and the correctness of final models generated by the participants. As shown in Fig. 5, the expert group generally outperformed the proficient participants in terms of both completeness and correctness. We tested the distribution of the two metrics between two groups of participants using one-tailed Mann–Whitney U tests with the alternative

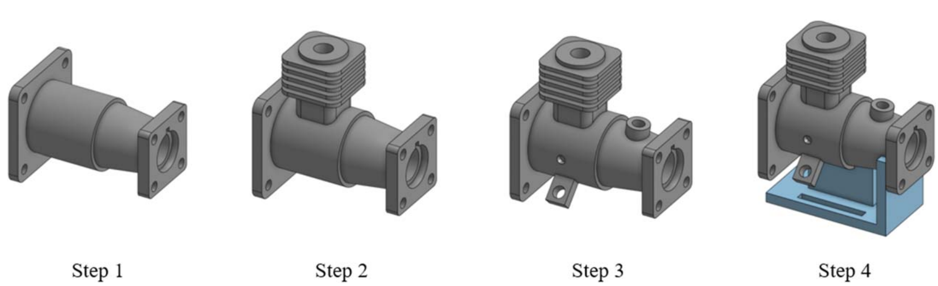

Fig. 4 Reference models by completion of each step of the modeling task. Step 1 establishes the main body feature and the flanges; step 2 adds the radiator feature; step 3 adds the tilted bore, angled tabs, and two small holes; and step 4 creates a supporting stand as a separate part.

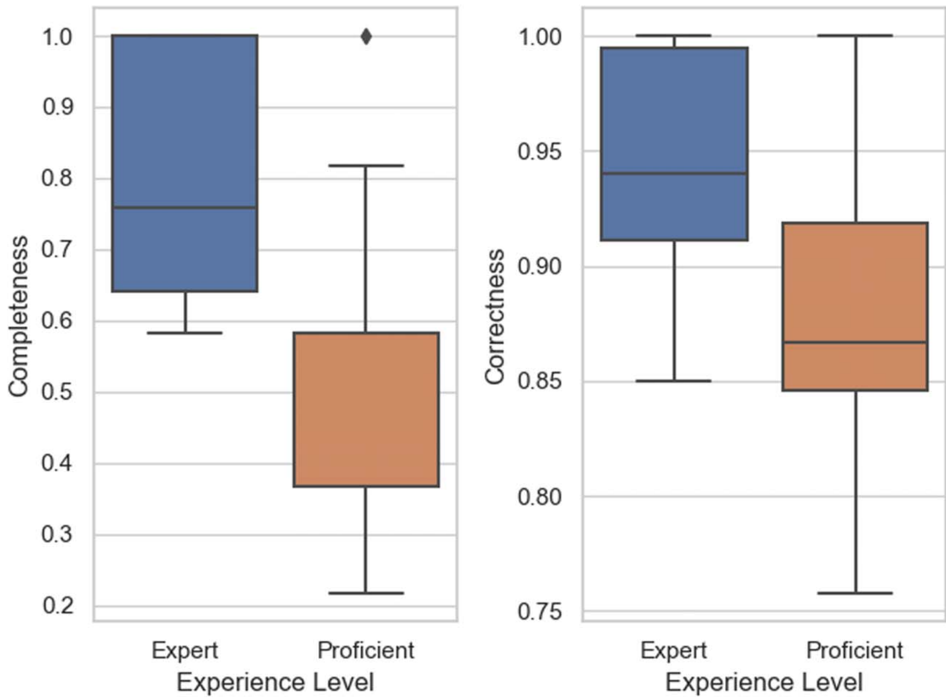

Fig. 5 Modeling performance of participants. The boxes show the quartiles of the dataset, and the whiskers extend to the rest of the distribution. Outliers that lie beyond 1.5 times the interquartile range are marked as points.

hypothesis stating that the expert group outperformed the proficient group. Specifically, there was a significant difference ($U = 73.0$, $p = 0.011$) in completeness between the experts ($\mu = 0.80$, $\sigma = 0.18$) and the proficient group ($\mu = 0.56$, $\sigma = 0.24$). Meanwhile, the difference between experts ($\mu = 0.94$, $\sigma = 0.053$) and the proficient group ($\mu = 0.88$, $\sigma = 0.075$) in correctness was also statistically significant ($U = 68.0$, $p = 0.032$). In other words, it was observed that the experts were able to finish a greater portion of the modeling task with higher accuracy. At the same time, the difference in task performance also demonstrated that participants' self-evaluated CAD experience level was indeed an effective measure to be used for subsequent analyses.

4.2 Action Counts and Time Spent. As enabled by the audit trail of the CAD platform, we were able to analyze all actions performed by the participants. Specifically, we counted instances of select actions to compare across participants, and with the start and end times also recorded, we were able to calculate the cumulative time spent on each of these actions. As presented in Table 1, we

Table 1 Action counts and time spent on the modeling task, standardized by individuals' completeness

Analysis type	Action type	Expert	Proficient	Comparison
Occurrence count	Create sketches	16.4 (4.26)	17.6 (4.37)	38.0
	Create features	33.2 (11.2)	28.0 (6.88)	56.0
	Edit sketches	11.1 (8.61)	14.1 (14.7)	37.5
	Edit features	11.1 (14.2)	9.82 (5.98)	38.0
	Cancel operations	12.4 (10.4)	24.8 (21.7)	18.0*
	Delete features	1.56 (2.36)	3.12 (4.07)	35.5
	Open drawings	72.3 (37.3)	108 (77.9)	26.0
	Undo/redo actions	4.07 (3.48)	20.2 (24.2)	19.5*
	Create folders	2.51 (4.02)	0.303 (0.909)	63.0
	Rename features	5.21 (12.9)	5.97 (16.2)	45.0
Time spent (s)	Create sketches	714 (395)	1289 (489)	20.0*
	Create features	550 (183)	625 (324)	39.0
	Edit sketches	183 (132)	855 (1676)	27.0
	Edit features	107 (139)	128 (82.5)	29.0
	Canceled creation	78.5 (58.2)	139 (73.2)	23.0
	Canceled edit	18.5 (25.8)	70.7 (72.4)	23.0
	Read drawings	734 (278)	1258 (671)	20.0*

Note: For both expert and proficient participants, the mean of the group was calculated with standard deviations reported in parenthesis. Comparisons between the two groups were made with two-tailed Mann–Whitney U tests, with the null hypothesis stating the distribution underlying sample x is the same as the distribution underlying sample y. * indicates $p < 0.05$.

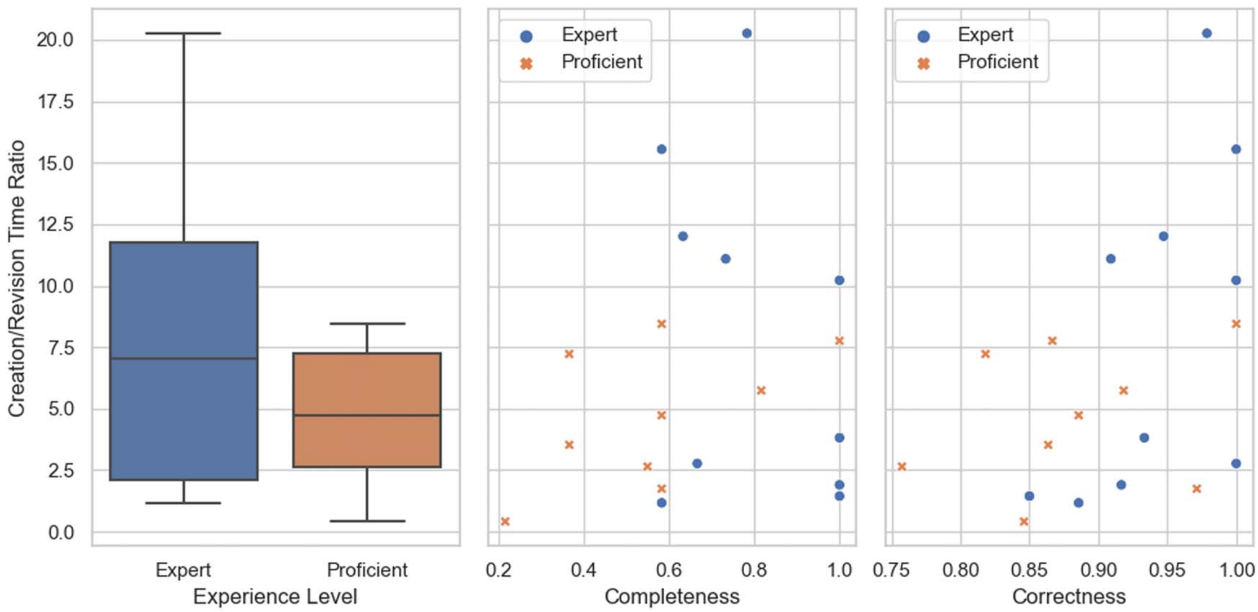

Fig. 6 Creation/revision time ratio of participants compared to expertise, completeness, and correctness. Participant creation/revision time ratio was found to be a statistically significant predictor of model correctness.

compared both the counts and time spent on actions, standardized by individuals' completeness percentages (a measure of their attempted progress through the task), between the expert and proficient participants in the modeling task with two-tailed Mann–Whitney U tests.

While users perform part modeling in CAD, there are typically two main types of constructive actions as outlined in Ref. [50]: sketching-related actions that work with 2D geometries, and other features-related actions that work with 3D solids (e.g., extrude, revolve, fillet). Earlier in the paper, experts were shown to be able to complete a larger portion of the modeling task under the same time constraint, however, results in Table 1 did not show significantly higher sketch or feature usage in either participant group. Experts did spend significantly less time in creating sketches. As this is an indication of more efficient sketch creation by the experts, it could further indicate more skillful design of sketch geometries for subsequent CAD features, highlighting forward planning when building a model.

Further, the experts also had significantly less occurrences of cancel operations and undo/redo actions. This is potentially a sign of more careful strategic planning before initiating an action. Consequently, although not statistically significant, this led to relatively less time wasted on canceled operations during the modeling process for the expert group. Similarly, the experts also spent relatively (not statistically significant) less time on editing the existing sketches and features.

Meanwhile, it was also noted that the experts spent significantly less time reading the manufacturing drawings, but with a very similar number of openings of the drawings when compared to the proficient group. This suggested that the experts were able to dissect the given problem and retrieve the needed information more efficiently during a similar number of referrals to drawings when rebuilding a model in CAD.

A comparison of the relative amount of time participants spent creating new features to the amount of time spent on revising existing features is visualized in Fig. 6. Comparing the difference in creation/revision time ratio between the expert and proficient participants, no significant difference was observed ($t(17) = 1.38$, $p = 0.184$). Next, we tried to correlate the creation/revision ratios to the two performance evaluation metrics that we defined for this experiment. It was first found that little correlation existed between the ratio and the completeness of a participant ($R^2 = 0.018$, $F(1, 17) = 0.31$, $p = 0.586$). However, a simple linear regression showed a significant correlation between participants' creation/revision ratios and their correctness in the modeling task. The fitted regression model suggests that

$$\text{Correctness} = 0.0061 \cdot \text{Creation/Revision Time Ratio} + 0.87$$

The overall regression was statistically significant ($R^2 = 0.225$, $F(1, 17) = 4.94$, $p = 0.040$), and the creation/revision ratio significantly predicted correctness ($\beta = 0.003$, $p = 0.040$). While a higher creation/revision time ratio indicates fewer revisions of previously committed CAD features during the modeling process, it also implies that participants who required relatively fewer revisions were able to finish the modeling task with higher dimensional

Table 2 Categorized actions in operation types (observable emissions in an HMM)

Emission #	Operation types	Categorized actions
1	Refer to drawing	Open one of the provided manufacturing drawings
2	Start creation	Begin the creation of a new CAD feature or sketch
3	End creation	Commit the creation of a new CAD feature or sketch
4	Start edit	Begin editing an existing CAD feature or sketch
5	End edit	Commit the edits to an existing CAD feature or sketch
6	Delete	Delete a CAD feature or sketch
7	Organize	Move a feature; rename a feature; create a folder

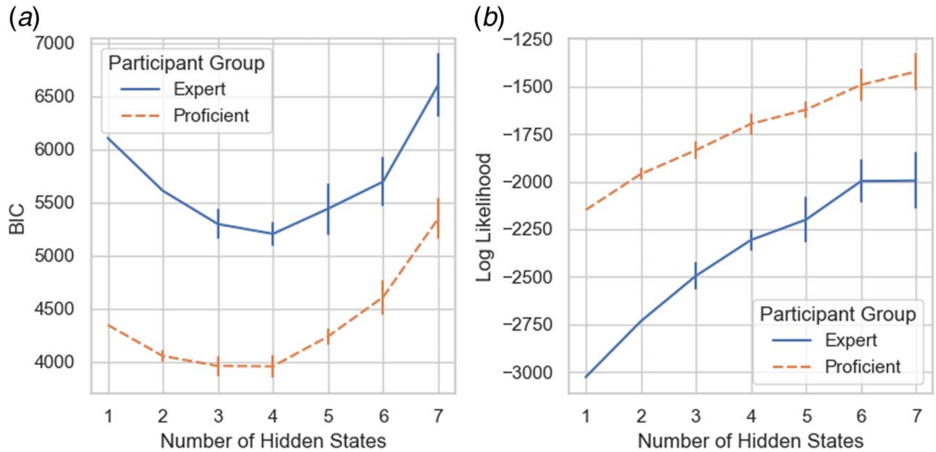

Fig. 7 Evaluation of HMMs with different numbers of hidden states on (*a*) BIC and (*b*) log-likelihood, used to select the optimized model with four hidden states for analysis. Error bars show standard deviations of HMMs trained with ten different random seeds for every number of hidden states tested, where each HMM was trained with 50 iterations.

accuracy. Meanwhile, spending a greater proportion of time on revisions during the modeling task does not generally result in higher accuracy of the final CAD model.

4.3 Transitions of Actions. To further explore the difference in modeling behaviors between the expert and proficient participants during the modeling task, we analyzed the transitions between consecutive actions using an HMM. As described in Sec. 3.5, we first categorized all the collected action types from participants' audit trail into a few operation categories, as shown in Table 2. Hence, each operation type corresponds to one observable emission type from the HMM. Specifying a discrete number of hidden states for an HMM, the model can be trained on the sequence of emissions derived from each participant's audit trail. While the maximum number of hidden states used should not exceed the number of emission types that the model is trained with [55], HMMs with a number of hidden states ranging from 1 to 7 were first trained with 10 iterations each. To determine the optimal number of hidden states to be used for the HMM for analysis, the Bayesian information criterion (BIC) of each model was computed, as shown in Fig. 7(*a*). As we aimed to use a model that has the best predictability (i.e., high log-likelihood as shown in Fig. 7(*b*)) without overfitting, we chose to use the number of hidden states that yielded the lowest BIC. Coincidentally, four hidden states were found to be optimal for both the expert and proficient group of participants in this experiment.

With the audit trail data of the expert and proficient participant groups each trained with an HMM with four hidden states, the resulting matrices are shown in Figs. 8 and 9, respectively. Comparing the two trained HMMs, differences in modeling behaviors can be observed through the probabilities of transitions and emissions of the hidden states. In the HMM for expert participants, start creating and start editing a feature were both categorized into one hidden state (i.e., state 1), and end creating and end editing a feature were both categorized into another hidden state (i.e., state 4).

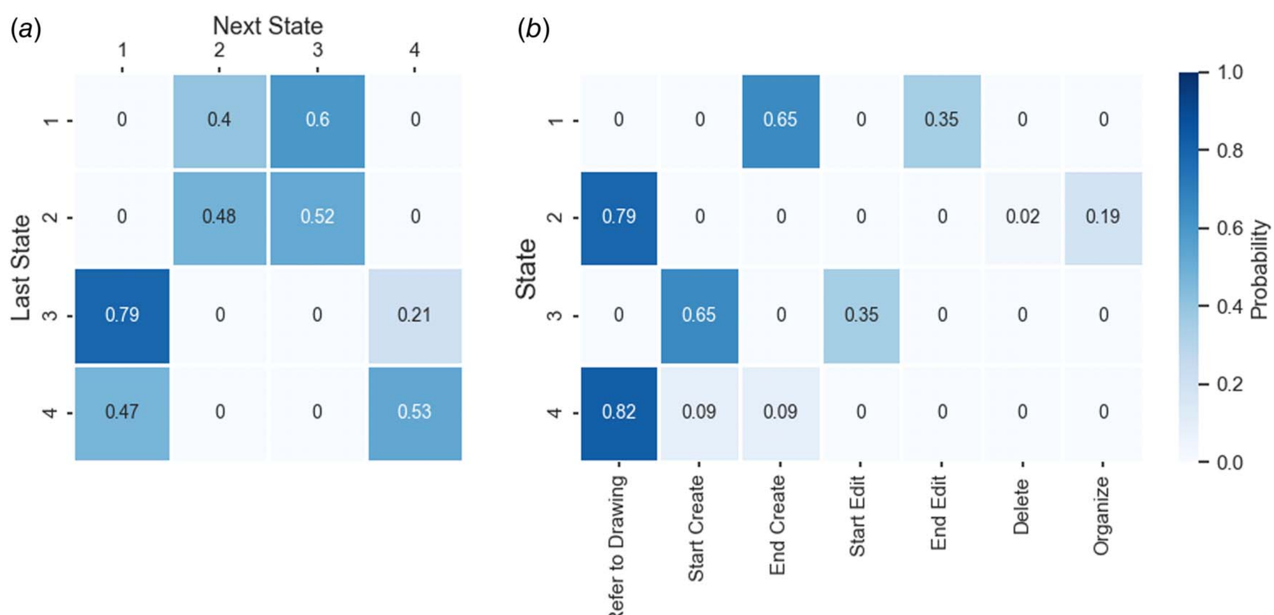

Fig. 8 (*a*) Transition and (*b*) emission probability matrices of an HMM modeling, the modeling process of the expert participants

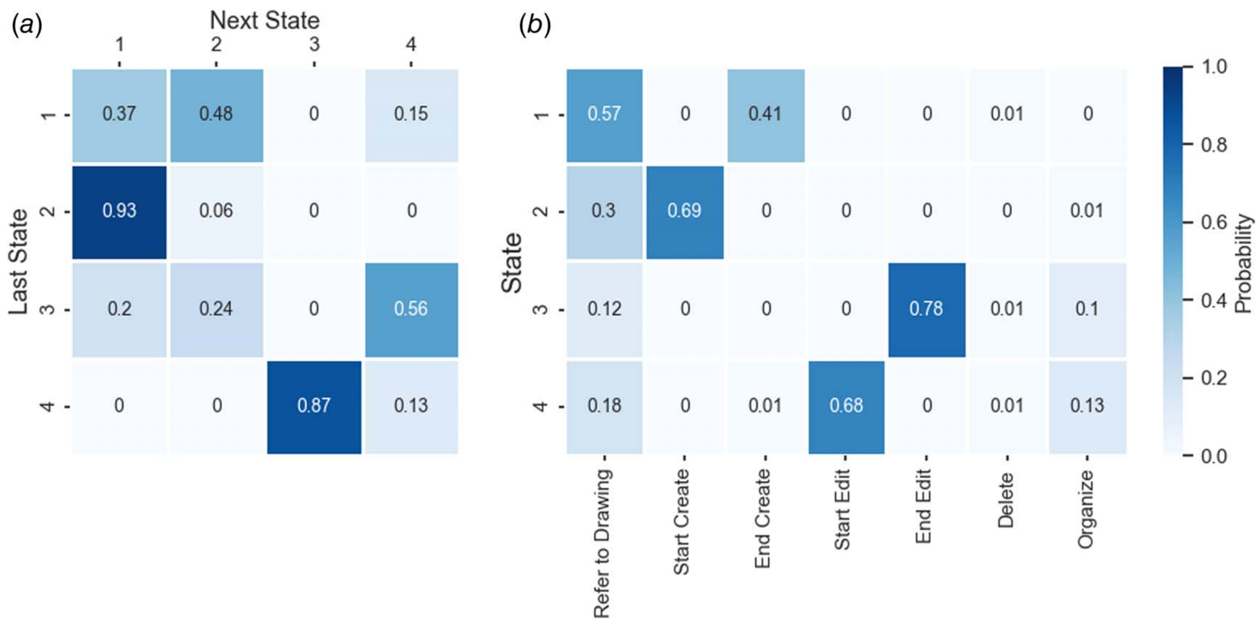

Fig. 9 (*a*) Transition and (*b*) emission probability matrices of an HMM modeling, the modeling process of the proficient participants

Meanwhile, the feature creation to editing occurrence ratio for expert participants was about 68% to 32%. On the other hand, "start create," "start edit," "end create," and "end edit" were each observed through one hidden state for the proficient participants. This difference in clustering of actions likely indicates that experts' feature creation and editing were likely performed similarly, where a more significant difference was observed for the proficient participants.

During the modeling process, all participants were requested to use only one screen to ensure consistency across participants. Thus, participants had to switch to the provided manufacturing drawings when referring to specific geometric dimensions. However, such behaviors were categorized differently into the four hidden states in an HMM between the expert and the proficient group. For the experts, state 2 and state 4 seemed to differentiate two types of referrals to drawings. Referrals observed through state 4 mainly occurred during a feature creation or edit (transitioned from hidden state 3 to state 4) with a 21% chance of occurrence after starting to create or edit a feature, which likely involved quick checks of specific dimensions during the construction of a CAD feature. Drawing referrals observed through state 2, however, mainly occurred after the creation or edit of a feature was completed (transitioned from hidden state 1 to state 2) with a 40% chance of occurrence after the creation or edit of a feature is completed, where the participants were more likely to plan out the next CAD feature to be implemented for the design. Further, the drawing referrals that likely involved design planning (i.e., state 2) also included 19% occurrences of organizing actions, where the participants likely cleaned up what they just finished creating or editing. For the proficient participants, on the other hand, "refer to drawings" were largely observed in nearly all four hidden states. This signifies that the proficient participants brought up the drawings in a less organized manner during the modeling process.

5 Discussion

5.1 Summary of Research Findings. In this paper, we present the findings from an experiment where professional CAD experts from the industry and young engineers with a proficient level of CAD experience were tasked with the same CAD modeling problem. We analyzed their individual modeling processes and compared the difference between the two groups of participants. After first evaluating the CAD models produced by the participants, it was confirmed that self-evaluated experts were able to complete a greater portion of the modeling task with higher dimensional accuracy under the same time constraint.

In general, experts in the experiment were observed to sketch more efficiently than proficient users. When modeling in CAD, the construction of sketches, especially the first few sketches, can largely influence the overall efficiency of the entire modeling process, because the creation of subsequent CAD features typically needs to reference geometries created by previous sketches. We might conclude therefore that while being proficient in modeling in CAD likely signifies a near-expert level of declarative knowledge in the use of specific features in CAD, the creation, and inferably the planning, of fundamental sketches is an element of procedural knowledge that requires more gradual development through one's career.

Meanwhile, models with higher dimensional accuracy were also recorded with relatively less time spent on the revision of existing features during the modeling process. Although the context of this study is solely constrained within the CAD platform, our findings resonate with Cross's conjecture that: "It may be that good designers produce good early concepts that do not need to be altered radically during further development; or that good designers can modify their concepts rather fluently and easily as difficulties are encountered during development, without recourse to exploration of alternative concepts" [17]. The need for more revisions may also be due to the lack of modeling strategies (i.e., the procedural knowledge), where participants likely relied on "trial and error" [21]. Rosso et al. also suggest that variability in the modeling process also affects the editability of the model in progress [18]. While designers often need to modify the existing CAD model during construction, superior modeling strategies continuously maintain the model in an editable state, reducing editing time and cost along the modeling process. The fact that experts had significantly less occurrences of undoing, redoing, and canceling actions in the modeling task is also indicative of a smoother modeling process. In any case, the proportional time spent on design revision over creation is one important component of the CAD modeling procedural knowledge that could be used to measure CAD expertise.

From the HMM analysis, the main distinction between the experts and the proficient CAD users was observed to be the ways they refer to the provided manufacturing drawings when modeling in CAD. While the trained HMM was able to clearly distinguish two types of referrals to drawing in the expert group, one during and one after feature creation or editing, similar trends could not be observed from the proficient group of participants. Representatively, an expert CAD modeler is less likely to open the drawing during a feature creation or editing process, where they typically refer to the drawing when they need to plan for the next steps. On the other hand, non-expert modelers tend to frequently switch back and forth between the workspace and the drawings. In fact, the experts spent significantly less time reading drawings, when the time spent was standardized by individuals' completeness in the modeling task. As summarized by Cross, successful design behavior is based not on extensive problem analysis, but on, among other things, a focused or directed approach to gathering problem information [17]. In our modeling task, reading and retrieving dimensions from the provided drawings may be representative of gathering information in a detailed design task, as may occur when a CAD designer is constrained by detailed specifications, competitor benchmarking, fidelity to physical prototypes, or requirements of interfacing parts. Thus, the more organized information retrieval behaviors from the experts likely reflect another important component of the CAD modeling procedural knowledge that differentiates CAD experts from others.

5.2 From Proficient to Expert in Computer-Aided Design. Based on our research findings, it can be concluded that the most significant difference between being proficient in CAD and being an expert in CAD centers around the mastery of procedural knowledge of the individual:

- With more industry experience, the experts can dissect the manufacturing drawings and gather geometric information in a way that requires fewer referrals back and forth between their CAD workspace and the drawings, thus spending less non-design time.
- As they start modeling in CAD, experts' superior procedural knowledge allows them to construct sketches more efficiently; these sketches play a crucial role in the creation of subsequent features in the modeling process.
- CAD modelers with higher accuracy tend to spend proportionally less time on feature revisions. This likely indicates more experienced declarative knowledge and smarter modeling strategies (elements of procedural knowledge), which eventually lead to a better-planned, and therefore efficient, modeling process.

From being able to extract information from manufacturing drawings to laying out the more efficient modeling approach before starting the modeling process, these are all skills that take time and practice to build, and they are not something that can likely be thoroughly taught with crash-course style learning within a short period of time. While improving one's procedural knowledge through trial-and-error experience can be time-consuming, recent research suggests the potential benefits and advantages of cognitive apprenticeship, where a master leads the apprentices through a modeling process by clearly describing the strategy that is being implemented [46]. It is important for engineering students and young engineers to understand not only the steps that are being performed but also how all the steps are planned for the entire modeling process. Meanwhile, this is not a habit that is easy to develop and stick with, where even a professional engineer would be tempted to use a well-structured plan opportunistically during the design process [60]. On the other hand, as further research better understands how experts design, there exists a promising potential for human-AI collaboration in design. With assistance from an AI agent, designers are expected to learn and work more efficiently in CAD by following the learned strategies from expert designers [9].

5.3 Limitations and Future Work. Several limitations in this study should be noted, where future work may be conducted. As we categorized participants for all analyses based on their self-reported experience with CAD, self-evaluations, in this case, cannot warrant accuracy and consistency across individuals. While two people may report an equal length of CAD experience, they likely used CAD with different degrees of frequency, intensity, and variety in different time periods. Further, it is common for people with lower competence to overestimate their skills in self-assessments [61]. Although results presented in this study did show a distinction in task performance between the two levels of experience, more reliable assessments of the participants can be conducted before the study for future research (e.g., assess participants' spatial abilities with the Purdue Spatial Visualization Test: Visualization of Rotations, as used in Refs. [30,62,63]). Further, future research will also benefit from having a larger and more diverse group of participants. As gender differences are traditionally observed in skills like spatial abilities [64], our current study is gender-imbalanced with 17 men and only 2 women.

In this study, all the actions studied were first categorized into a smaller number of groups before further analyses. This preprocessing method of the data provided greater efficiency of analysis and interpretability of the results. However, it can arguably overlook some details of the modeling process. Future work could further seek meaningful differences by studying user actions and tendencies in greater detail. For instance, features used in CAD can be further categorized into additive, subtractive, and refinement features, helping to further pinpoint expert strategies. While we see evidence that the experts better establish their CAD models with initial sketches, we can dig deeper to understand if there are systematic characteristics that set these sketches apart. For example, future work can examine the CAD model artifact (e.g., the geometries of each sketch, the parameters for each feature, and the parametric dependencies of sketches and features). The inclusion of richer data types can enable HMM analysis with more emission types for us to study the modeling process more closely, and the correlation between the parametric data and behavioral actions may also yield interesting research findings. Meanwhile, a larger dataset with more participants may also increase the log-likelihood (i.e., the generality) of the trained HMM with potential applications for building a recommender system to predict or recommend the next feature to be used for the user, similar to the work shown in Refs. [11,56,57].

Nowadays, our experimental task—re-modeling a 3D solid part in CAD based on 2D drawings—has been a widely adopted approach for nearly all commercially available CAD software to test their users on mastery of their products, and users' abilities in CAD. However, there exist limitations to this format of testing. In fact, real-world design problems are mostly ill-structured and ill-defined. In that scenario, the most prominent difference between experts and novices was found to be the strategy used to decompose the problems [24]. Although an open-ended design component was not included in our modeling task, a similar difference was also observed in how participants with different experience levels decomposed and referred to the dimensions of the given drawings (i.e., the "problem" in this experiment) before and during the modeling process. In future studies that span through the conceptual and detailed design phases, it will be interesting to evaluate how much advantage such effective problem decomposition strategies provide.

While we aimed to provide a consistent, comfortable, and non-intrusive experimental setting which would match that typically encountered in an industrial CAD setting, one notable difference in our experiment is that we asked participants to use only one screen during the modeling process (e.g., no "dual-monitor" setups). This was necessary in this experiment to control the consistency across participants and to track the actions of referrals to drawings. This difference may inflate our perception of the importance of referral to drawings.

Finally, a designer in industry would typically be faced with a CAD modeling task accompanied by information on the intended use or manufacturing process of the product, which was not given in the experiment, such that we could isolate CAD modeling and not context or manufacturing knowledge. Future research is needed to investigate how different design intents expressed in drawings affect the modeling process.

6 Conclusions

In this paper, we closely examined the difference in the modeling process between expert and proficient CAD users when modeling the same mechanical part in the same setting. Under an identical time constraint, self-identified experts were able to complete a greater portion of the modeling task with higher dimensional accuracy. Detailed analysis of the modeling process suggested a significant difference in modeling strategies between the two groups of participants. Beyond mastering CAD features in a specific design software, we found that (1) experts were better at reading and dissecting manufacturing drawings when modeling, and (2) experts were able to plan their CAD features ahead and select a more efficient modeling strategy that required less effort and revisions. While it takes time and practice for young engineers to develop these skills to bridge the gap and become design experts, the experimental study of this experience gap delivers first-of-its-kind insight into CAD expertise and builds on the understanding of expert modeling behaviors in general. Eventually, this knowledge can be used to develop future smart assistants and contribute to more effective curricula and training in design.

Conflict of Interest

The authors declare the following conflict of interest: the lead author on the paper was an intern at the company PTC during the writing of this paper. PTC is the provider of the CAD software ONSHAPE, used in this experiment for data collection. PTC has also supported the final author's research group with a research and teaching gift.

Data Availability Statement

The datasets generated and supporting the findings of this article are obtainable from the corresponding author upon reasonable request.

Appendix A: Drawings Provided for the Modeling Task

The manufacturing drawings that were used and provided to the participants for the four steps of the modeling task are presented in Figs. 10–14.

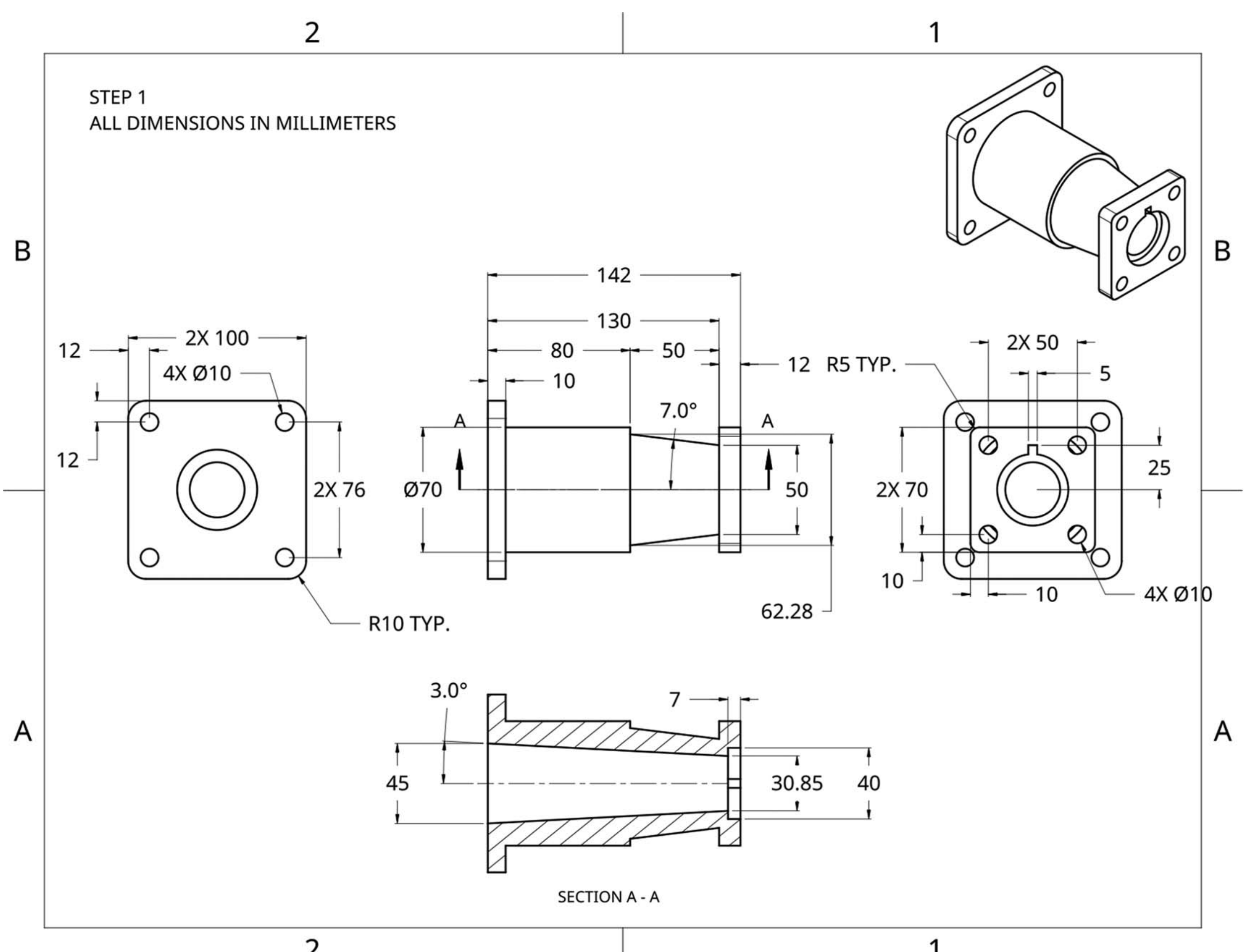

Fig. 10 Drawing provided for step 1 of the modeling task

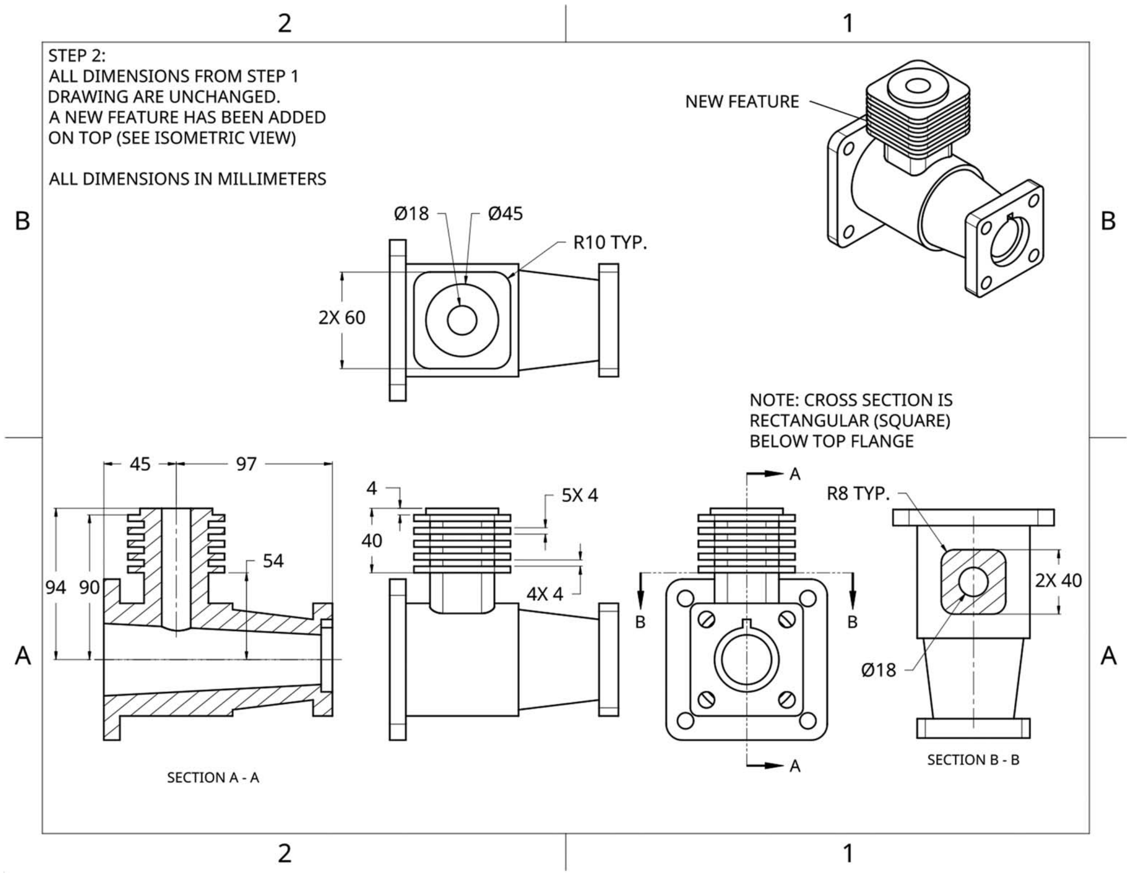

Fig. 11 Drawing provided for step 2 of the modeling task

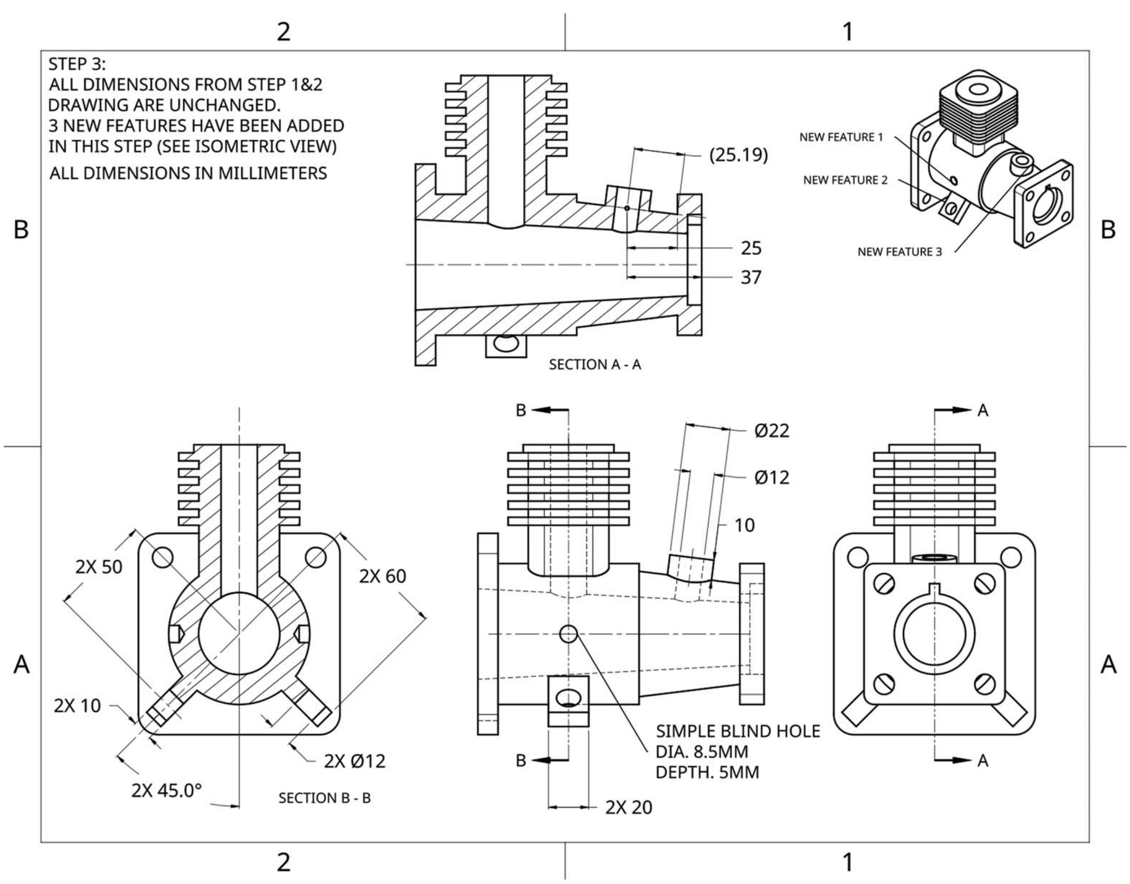

Fig. 12 Drawing provided for step 3 of the modeling task

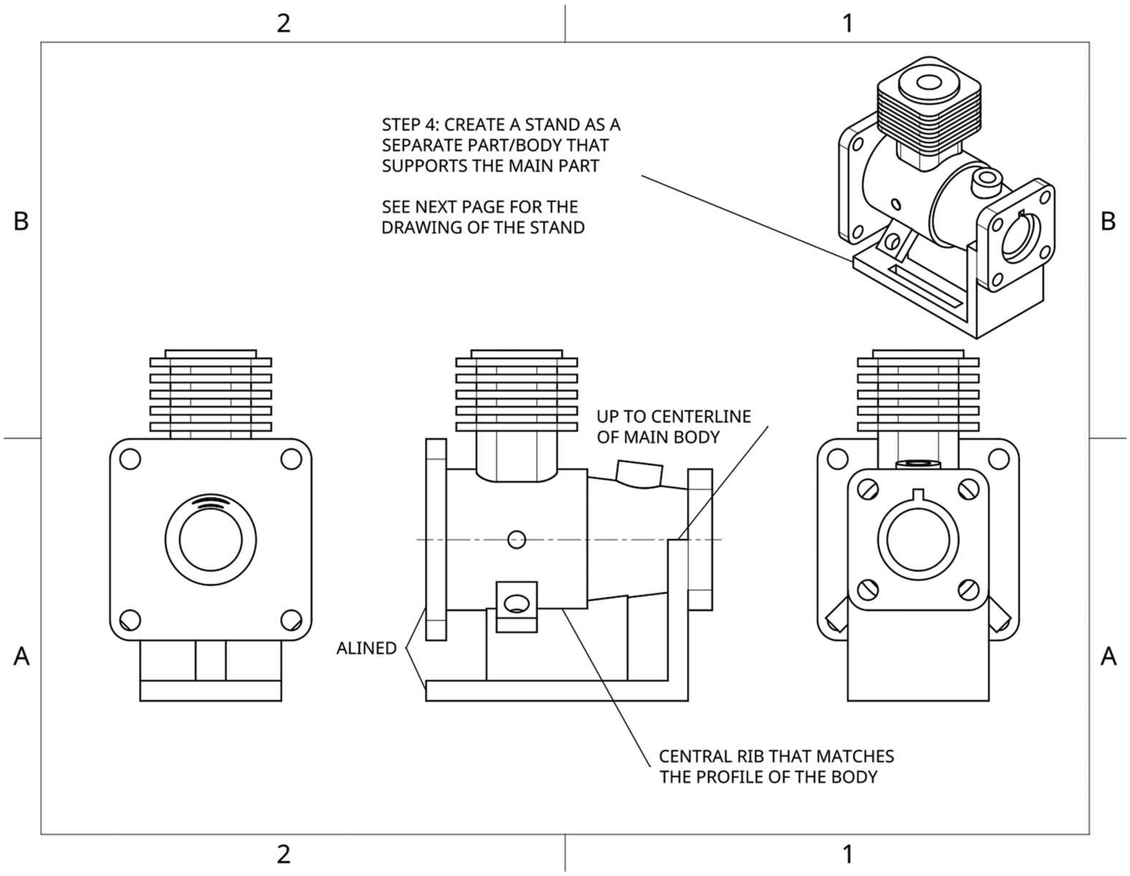

Fig. 13   Drawing provided for step 4 of the modeling task (page 1 of 2)

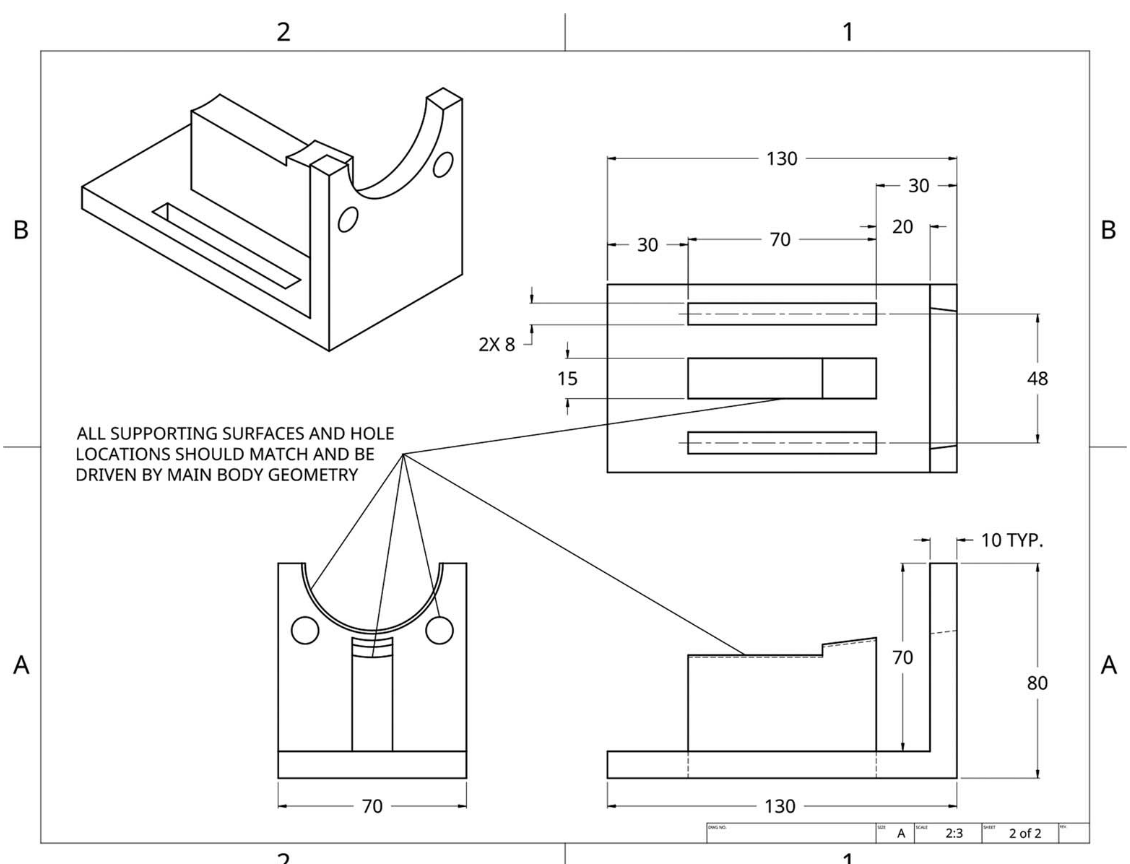

Fig. 14   Drawing provided for step 4 of the modeling task (page 2 of 2)

Appendix B: Drawings for Grading

A different version of the same drawings provided to the participants was used for the grading of participants' completeness and correctness. These drawings contain the minimum number of dimensions and constraints that can fully define the parts. Drawings used for the four steps of the modeling task are presented in Figs. 15–18.

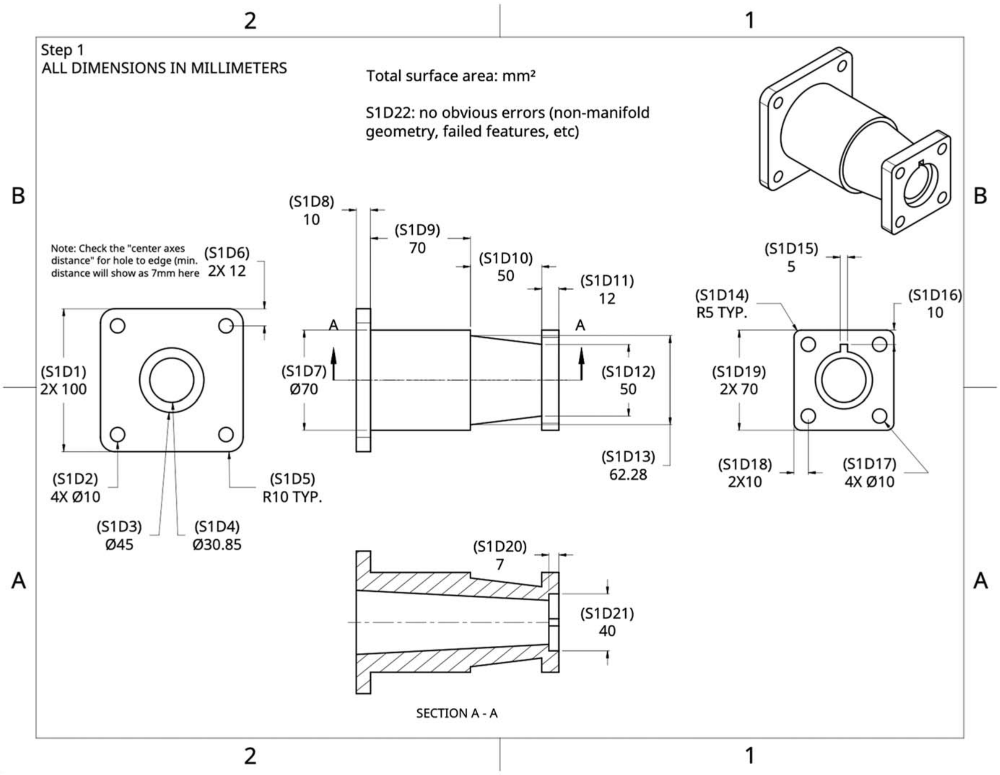

Fig. 15 Drawing used for grading step 1 of the modeling task

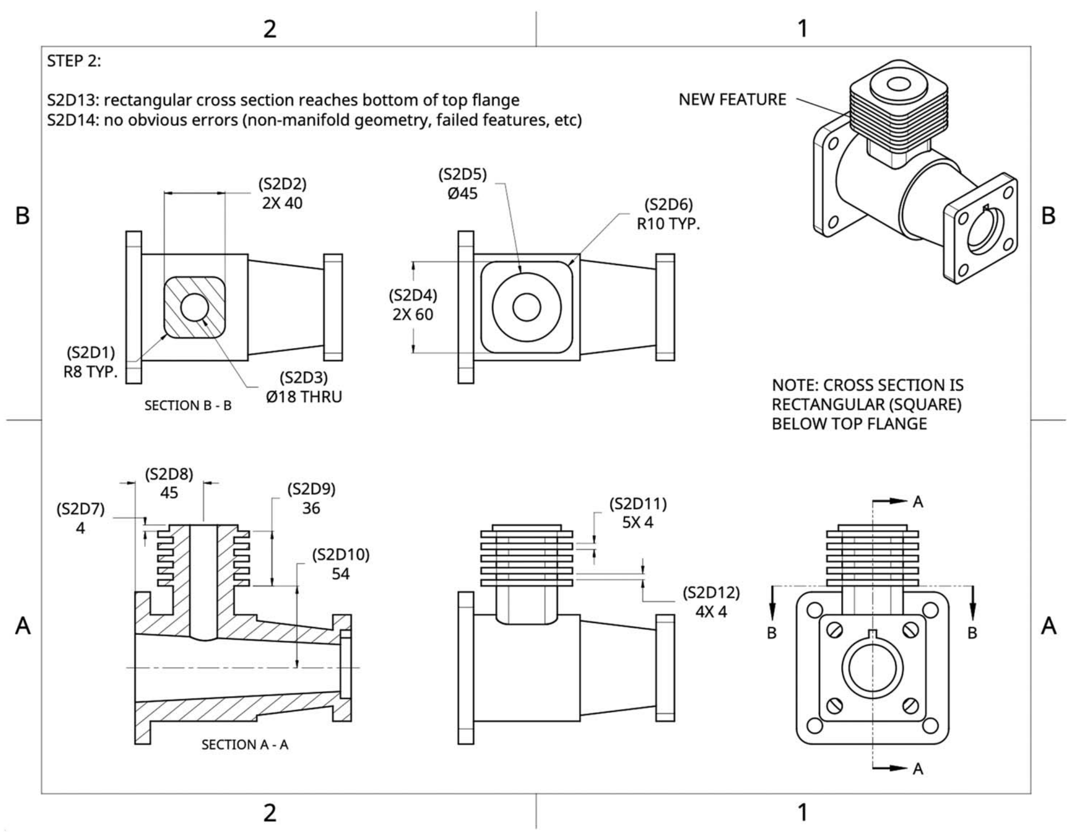

Fig. 16 Drawing used for grading step 2 of the modeling task

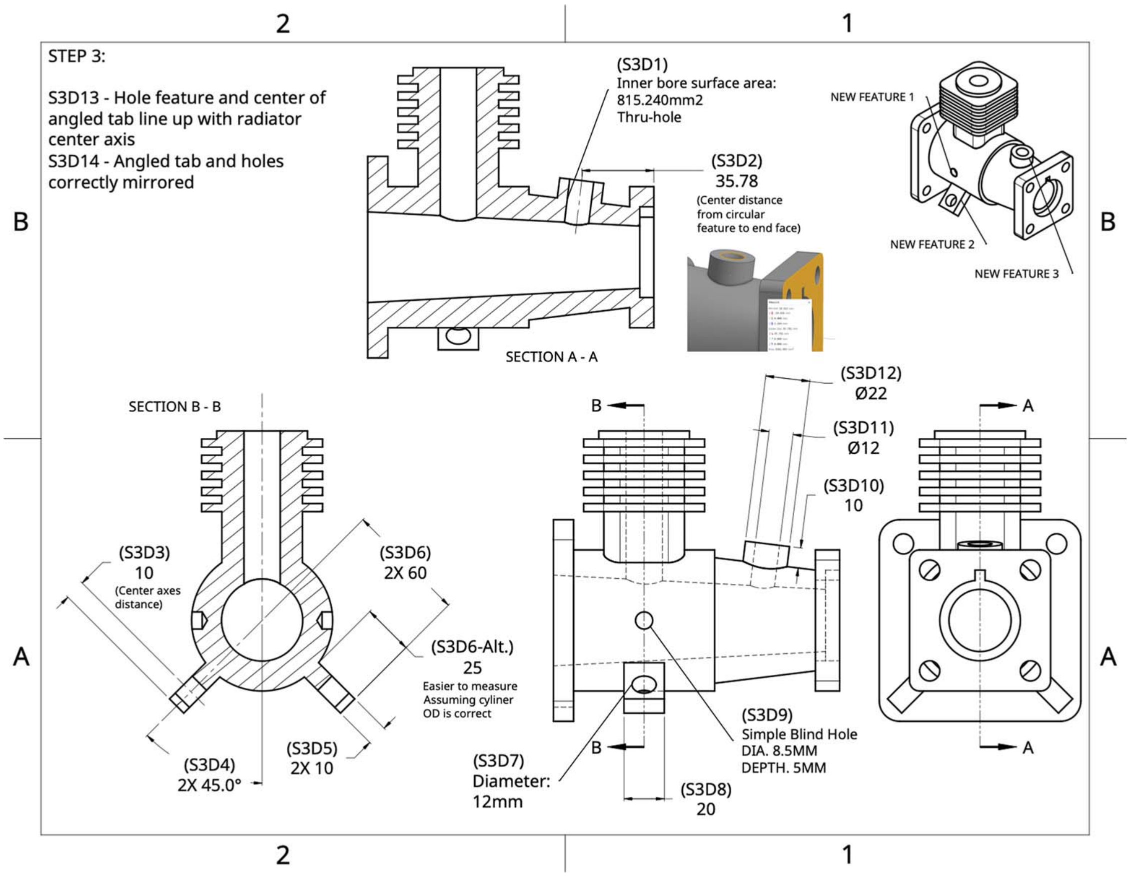

Fig. 17 Drawing used for grading step 3 of the modeling task

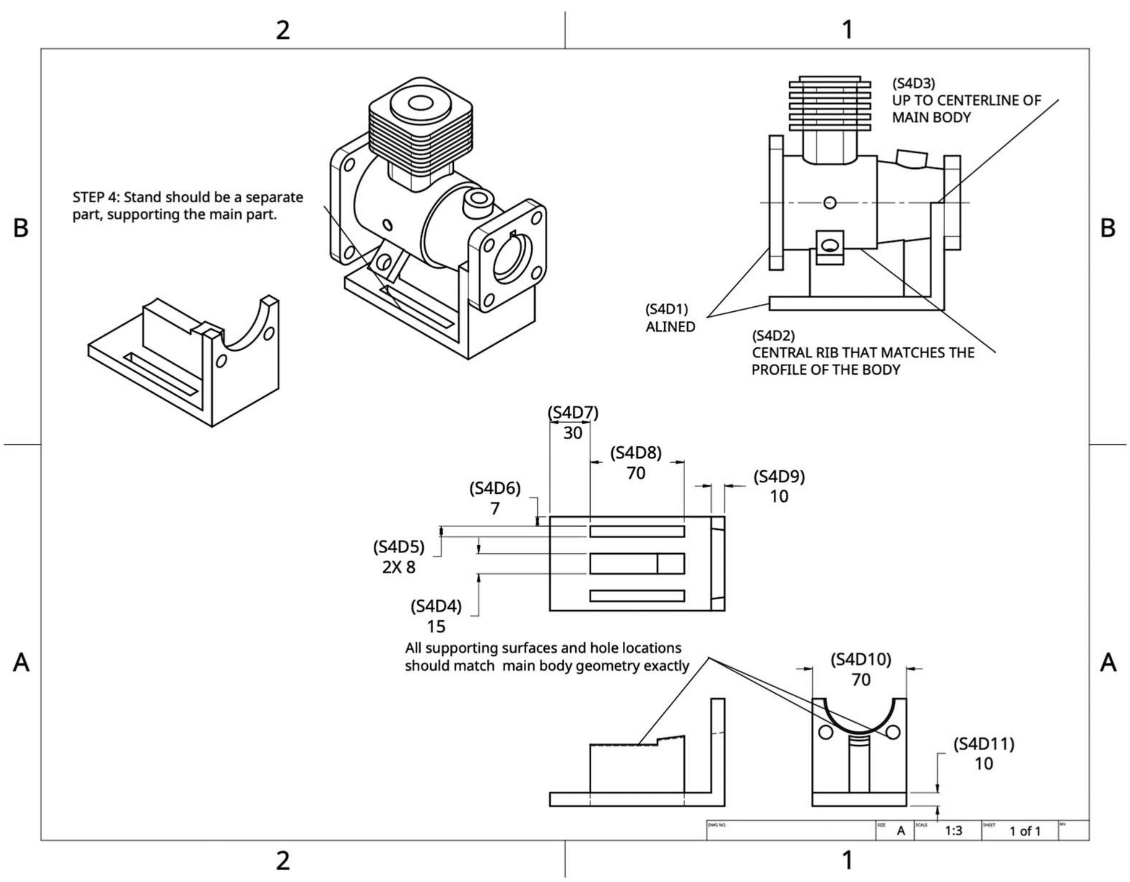

Fig. 18 Drawing used for grading step 4 of the modeling task

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