Examining the Role of Contextual Exercises and Adaptive Expertise on CAD Model Creation Procedures

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Abstract. As computer-aided design (CAD) tools become more integral in the product commercialization process, ensuring that students have efficient and innovative expertise necessary to adapt becomes more important. This work examines the role of adaptive expertise on CAD modeling behavior and the effect of contextual modeling exercises on the manifestation of behaviors associated with adaptive expertise in a population of student participants. A methodology comprising multiple data elicitation tools is used to examine these relationships; these tools include: survey data, model screen capture data analysis, and interviews. Results show that participants engaged in contextual exercises spent more of their modeling time engaged in actual modeling activities as opposed to planning when compared to a control group. Limited statistical support is provided for the role of contextual exercises leading to the manifestation of behaviors associated with adaptive expertise. The amount of time spent engaged in actual modeling is positively correlated with the adaptive expertise behaviors identified in the interviews.

Keywords: Adaptive Expertise, CAD, Evaluation Methods and Techniques, Modeling Processes.

1 Introduction

Students today will enter an industrial environment where computer-aided design (CAD) models are a nexus for the product commercialization process. These tools, when used along with product lifecycle management systems facilitate the efficient execution of complex development projects [1-4]. It is important that students are able to competently and efficiently use CAD tools; this is especially true given these tool's skill driven nature [5]. While students will likely gain CAD experience during their engineering education, the CAD tools they find in industry will probably not be the same ones used by their institution. Even if the CAD platform is the same, there are often numerous and significant updates associated with CAD platforms. An additional concern is the typical educational focus on declarative knowledge; these are the specific procedures required to carry out tasks in specific CAD platforms [6, 7]. This is in

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contrast to strategic knowledge which is associated with general CAD expertise and has been shown to be transferable to other CAD platforms [8]. Namely, this expertise is adaptable. Adaptive expertise is defined as the ability to apply knowledge in new situations when key parts of that knowledge are missing [9]. Expertise can be categorized as either routine or adaptive in nature [10]. While routine experts are efficient in the domain of their expertise, adaptive experts are both efficient and innovative. Schwartz et al.,[11] propose that learning exercises be developed which promote both efficiency and innovation; these would promote adaptive expertise. It is thought that adaptive experts seek new learning opportunities, monitor their understanding and thinking, and view knowledge as more dynamic [11]. These characteristics are thought to make adaptive experts flexible, innovative, and creative particularly in novel situations [12].

Students are rarely provided with curricular activities that would promote the competencies associated with adaptive expertise [12]. The lack of opportunities for self-learning in engineering curricula has been noted [13]. Contextual exercises have a documented positive impact on students' cognitive and affective domains [14]. Students learn more effectively when they engage in activities that have personal meaning; with respect to CAD education, this may mean modeling objects connected to daily life or personal interest. This work seeks to examine two causal relationships: the effect of adaptive expertise on CAD modeling procedure and the effect of contextual exercises on the manifestation of behaviors associated with adaptive expertise. Multiple knowledge elicitation methods are used to examine these relationships and are described in the next section.

2 Methods

The data presented in this work are the result of a one semester examination of adaptive expertise and the role of contextual exercises in a combined product design and CAD course at Texas A&M University. A total of 32 students took part in some aspect of the exercise. Some student did not complete or consent to certain parts of the exercise; these cases are noted in the results section.

2.1 Adaptive Expertise Survey

One of the main goals of this work is to assess the relationship between adaptive expertise and CAD modeling. As such, the first step was to assess baseline adaptive expertise among the student population. As stated above, adaptive experts have characteristics that distinguish them from their routine counterparts. Fisher and Peterson [15] define four main constructs of adaptive expertise: multiple perspective, metacognition, goals and beliefs, and epistemology. Their work uses a 42 question, 6-point Likert-scale, instrument to assess the adaptive expertise of biomedical engineering students. This work has adopted their instrument to assess the adaptive expertise of the student population prior to the modeling exercise.

A subset of the 42 questions was used to determine dimensional scores using exploratory and confirmatory factor analysis. These analyses used a combination of almost 200 respondents to the survey and included both practicing engineers and students. The original four constructs of Fisher and Peterson [15] were maintained. The questions used for each construct were: multiple perspectives (5, 13, 34,36, 39); metacognition (2,6,10,14,26,30); goals and beliefs (3,7,23,27,38,41), and epistemology (12, 33). These questions were then averaged to determine a sub-score for each construct as well as an overall adaptive expertise score from the average of all 19 questions.

2.2 CAD Modeling Exercise

The purpose of the CAD modeling exercise was twofold: the first goal was to provide a modeling exercise with which to compare baseline adaptive expertise; the second was to evaluate the role of contextual exercises on both modeling behavior and the expression of behaviors associated with adaptive expertise. The modeling exercise took place after the adaptive expertise survey instrument had been administered. The students in the course were split into two groups based on their performance on a lab exercise (to ensure similar skill levels in each group): one group (control) was given a stylized exercise similar to one found in a CAD textbook [16]; the other group (contextual) was asked to bring in an object of moderate complexity they were familiar with to model. The contextual group students were given a ruler to determine dimensions from their object; all dimensions associated with the control object (a drawing) were given. Figure 1 shows the drawing and CAD model screenshot for the control group; Figure 2 shows the contextual object and a CAD model screenshot. Students were given one hour to complete the modeling exercise. During the exercise, the Camtasia screen capture software was used to record participant screens.

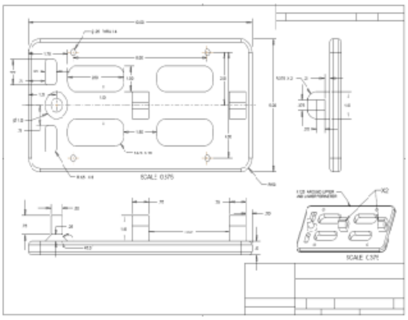
2.3 Interview

Both prior to and immediately following the CAD modeling exercise, pre- and post-interviews, respectively were conducted. The pre-interview questions included:

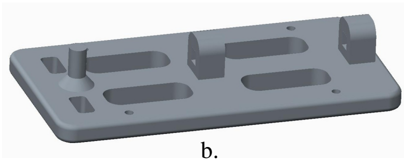
- What are the things you consider first when you are asked to model an object? Why?
- What are the challenges you often encounter in the modeling process?
  - How do you plan to overcome these challenges?
  - Which strategies do you anticipate using?
- Are you familiar with the object you are going to model today?
- How important it is to know about the object you are going to model?
  - If you are familiar with the object you are modeling or if you use it often in your daily life, is it easier for you to model it? Why, why not?

The post-interview questions included:

- The things you considered before you began modeling the object, were they helpful to you in the process? How and why?
- What challenges did you encounter during the modeling process?
  - How did you overcome the challenges you faced during the modeling process?
- Was knowing the object or being familiar with it, helpful to you in your modeling process? How and why?
- How confident are you in your model?



a.



b.

Fig. 1. Control item drawing (a.) and screen shot of control CAD model (b.)

a. b.

Fig. 2. Contextual item (a.) and screen shot of example contextual CAD model (b.)

The interviews were audio recorded and transcribed verbatim. The constant comparative method was used to analyze the transcripts [17, 18]. First open and axial coding was used to analyze the interview responses. Next selective coding was used. The responses were coded along the four dimensions of adaptive expertise defined by Fisher and Peterson [15]. This coding was based on adaptive expertise characteristics; these codes, characteristics, and their associated dimensions are shown in Table 1. Pre- and post-interview instances for each dimensions were tabulated and used to determine an overall pre-, post-, and total interview adaptive expertise manifestation counts.

2.4 Model and Procedure Analysis

The modeling procedures of the student participants were examined in two ways. The first entailed the analysis of model and feature characteristics as detailed in Johnson

Table 1. Codes extracted from the interviews and the associated adaptive expertise dimensions

Dimension	Characteristics	Codes from Interviews.
Multiple Perspectives	Efficiency (consistency & accuracy)	• most efficient way to model • easiest way to model
	Innovation	• N/A
	Act flexibly to novel situation	• creating drawing of object
Metacognition	Confidence	• N/A
	Successfully monitor own understanding	• have to pay close attention while modeling • have a good starting point • in hand 3D part helps
	Recognize that own knowledge may be incomplete	• how to use the features • complexity of the object • how to model • forgot how to use some features
	Use different / multiple methods to solve problem	• creating drawing of object • look object from different angles • trying different methods
Goals & Believes	Seek out opportunities for new learning	• try to learn better (if you had problems)
	Self-regulation strategies	• have an approach • have a way to organize model • know what steps to take first • have a good starting point • have strategies to model
Epistemology	Pursue knowledge	• practice • reading more
	Others can provide information	• ask someone for help

and Diwakaran [19]. These included the number of features, amount of reference geometry used, incorrect feature terminations, the number of segments per feature (a proxy for feature complexity), and the number of weak dimensions. Interested readers are referred to Johnson and Diwakaran [19] for detailed definitions of these quantities.

The second way of examining modeling procedure consisted of using the Camtasia screen capture videos of the students modeling to assess how they used their time during the modeling process. The time was split into three main categories: thinking, searching, and doing. Thinking or planning time was deemed to be anytime that there was no cursor movement in the video. Searching time was that where students were looking for specific functions or tools; this was defined by the non-performance of any modeling action. Finally, doing time was defined by the participant engaging in a particular modeling procedure; time was coded as doing even if the participant later deleted or changed the original work. An additional waiting category is used for time that the system is processing data or model changes. The data elicited from these various methods was correlated with the original adaptive expertise survey data; an analysis of the data between the control and contextual groups was also performed.

3 Results

To examine the role of contextual exercises on modeling behavior and the manifestation of behaviors associated with adaptive expertise, results for the control and contextual groups were analyzed and compared using t-tests. Table 2 shows a summary of the data for the two groups; results that are significant at the $p \leq 0.10$ are bolded. Only participants that completed their modeling exercise are included in the data presented. Out of a total of 32 participants, 21 completed their modeling exercises (11 from the control group; 10 from the contextual group). As mentioned previously, student groups were formed based on their performance on a previous exercise. However, to provide a baseline comparison adaptive expertise survey data are shown for the two groups. An unexpected result is the statistically significantly higher score on the epistemology dimension for the control group. The survey results for the other dimensions were comparable.

Students assigned to the contextual exercise took a statistically significantly longer time to complete the exercise than their counterparts in the control group. One possible explanation for this could be that participants in the contextual group had to derive the dimensions for their component, while those in the control group had their dimensions provided on the drawing. This is not the case. The mean thinking time (which one would assume would contain dimensioning time) for the contextual group was 6.15 minutes (SD = 3.24) and that for the control group was 7.90 minutes (SD = 2.78). The number of features used in the control group was greater than that of the contextual group. The contextual group also used more reference geometry features; this was a statistically significant difference. However, given the variety of components used in the contextual group, these two result (features and reference geometry) are not meaningful. The feature density for the two groups was comparable. Higher feature density has been viewed as a proxy for modeling skill or expertise [6]. The contextual modeling group had less incorrect feature terminations, but produced models that had more weak dimensions. The contextual group spend a statistically significantly higher percentage of their modeling time doing actual modeling as compared to the control group. This relationship was reversed in the percent thinking category where the control group spent more time thinking.

The final comparison comprised pre and post interview data related to the manifestation of behaviors associated with adaptive expertise. The pre-exercise interview data related to multiple perspectives and goals and beliefs were higher for the contextual group than the control group; however, these differences were not statistically significant. The total pre-exercise data was also higher for the contextual group, but again this difference was not statistically significant. The post-exercise data related to metacognition and the overall post-exercise count of behaviors are both statistically significantly higher for the contextual group. The overall interview data related to the

Table 2. Comparison of variables for control and contextual modeling exercises

	Control	**Contextual**	***t***	***p***
Number of Students participating	16	16	-	-
Students Completing Exercise	11	10	-	-
Survey Data				
Epistemology	5.00	3.95	**2.60**	**0.012**
Goals and Beliefs	3.61	3.37	0.59	0.562
Multiple Perspectives	3.66	4.04	-1.31	0.204
Metacognition	4.62	4.42	0.70	0.490
Total Adaptive Expertise	4.09	3.94	0.62	0.542
Model and Procedure Data				
Completion Time	37.6	53.6	**-3.12**	**0.006**
Number of Features	19.64	14.30	1.39	0.181
Reference Geometry	0.45	2.00	**-1.78**	**0.090**
Incorrect Feature Terminations	4.27	1.60	1.70	0.106
Average Number of Segments	3.20	2.88	0.42	0.681
Total Number of Weak Dimensions	7.09	17.40	**-2.58**	**0.018**
Percent Doing	71.5%	83.9%	**-3.81**	**0.001**
Percent Searching	7.3%	4.6%	1.01	0.327
Percent Thinking	21.2%	11.3%	**3.66**	**0.002**
Percent Waiting	0.0%	0.3%	-1.64	0.118
Interview Data				
Pre- Multiple Perspectives	0.10	0.57	-1.72	0.105
Pre- Epistemology	0.30	0.29	0.05	0.963
Pre- Metacognition	1.10	1.00	0.22	0.830
Pre- Goals and Beliefs	0.50	0.86	-0.92	0.373
Pre- Total Adaptive Expertise	2.00	2.71	-1.27	0.222
Post- Epistemology	0.10	0.00	0.83	0.420
Post- Metacognition	0.10	0.71	**-2.32**	**0.035**
Post- Total Adaptive Expertise	0.20	0.71	**-1.80**	**0.092**
Interview Total Adaptive Expertise	2.20	3.43	-1.67	0.115

exercise was also higher for the contextual group; however, this difference was not statistically significant. This lends limited support to the role of contextual exercises increases the manifestation of behaviors associated with adaptive expertise.

To examine the role of adaptive expertise on modeling behavior, survey data correlations with model and procedure variables were examined. These correlations were examined for the contextual data, the control data, and the overall data set (combining both control and contextual). For participants in the contextual exercise, the epistemology dimension of the survey was negatively correlated the percent thinking time ($N = 10$, $r = -0.670$, $p = 0.034$). Contextual exercise participant data also showed a positive correlation between the multiple perspective dimension and the percent thinking time ($N = 10$, $r = 0.566$, $p = 0.088$). Neither of these correlations was statistically significant for either the control data or the overall data set. The epistemology dimension of the survey was positively correlated with the number of features for both the control group ($N = 11$, $r = 0.610$, $p = 0.046$) and the overall data set ($N = 21$, $r = 0.474$, $p = 0.030$); the correlation for the contextual group was not statistically significant. There was a negative correlation between the goal and beliefs survey dimension and the number of features for both the control group ($N = 11$, $r = -0.722$, $p = 0.012$) and overall population ($N = 21$, $r = -0.422$, $p = 0.057$); again the correlation for the contextual group was not statistically significant. The overall survey measure of adaptive expertise was negatively correlated with the number of features for the control group ($N = 11$, $r = -0.541$, $p = 0.086$). The multiple perspective measure was negatively correlated with the number of features used for the overall data set ($N = 21$, $r = -0.373$, $p = 0.095$). The lack of correlations between adaptive expertise measures and features related to the contextual exercises is understandable given the wide variety of components that were modeled in the contextual exercise group. Next, instances of adaptive expertise data derived from interview data were compared to model attributes and modeling procedure data. It should be noted that not all participants consented to interviews; this lowers the sample number. For the contextual exercise group the following correlations were statistically significant: pre-interview metacognition and the number of weak dimensions ($N = 7$, $r = -0.689$, $p = 0.087$); pre-interview goals and beliefs and the number of reference geometry features ($N = 7$, $r = 0.738$, $p = 0.058$); post-interview metacognition and the number of incorrect feature terminations ($N = 7$, $r = -0.679$, $p = 0.093$); and the post-interview total and the number of incorrect feature terminations ($N = 7$, $r = 0.679$, $p = 0.093$). For the control exercise group the following correlations were statistically significant: pre-interview metacognition and the number of features ($N = 10$, $r = 0.754$, $p = 0.012$); post-interview epistemology and the number of features ($N = 10$, $r = 0.989$, $p < 0.001$); post-interview epistemology and the number of segments per feature ($N = 10$, $r = -0.608$, $p = 0.062$); and the post interview total and the number of features ($N = 10$, $r = 0.683$, $p = 0.029$). Finally, for the entire data set, the following correlations were statistically significant: pre-interview goals and beliefs and the number reference geometry features ($N = 17$, $r = 0.525$, $p = 0.030$); post-interview epistemology and the number of features ($N = 17$, $r = 0.909$, $p < 0.001$); post-interview epistemology and the number of incorrect feature terminations ($N = 17$, $r = 0.486$, $p = 0.048$); post-interview metacognition and the number of reference geometry features ($N = 17$, $r = 0.445$, $p = 0.074$); and post-interview metacognition and the number of weak dimensions ($N = 17$, $r = 0.501$, $p = 0.041$). For the contextual exercise group, the statistically significant correlations between interview data and modeling procedure included: the total number of interview adaptive expertise manifestations and the percentage doing time ($N = 7$, $r = 0.828$, $p = 0.021$); and the total number of interview adaptive expertise manifestations and the percentage thinking time ($N = 7$, $r = -0.874$, $p = 0.010$). There were no statistically significant correlations of note for the control group. The overall data also had statistically significant correlations for the total number of interview adaptive expertise manifestations and the percentage doing time ($N = 17$, $r = 0.439$, $p = 0.078$) and percentage thinking time ($N = 17$, $r = -0.537$, $p = 0.026$).

4 Conclusions

This work examined the role of adaptive expertise on CAD modeling procedure and the effect of contextual exercises on CAD modeling procedure and the manifestation of adaptive expertise. Prior to the modeling exercise, participants were administered a survey to assess their adaptive expertise on four dimensions: multiple perspective, metacognition, goals and beliefs, and epistemology [15]. A student population was divided into a control group, which received a stylized component drawing of moderate complexity and a contextual group, which modeled an item of intermediate complexity with which the participant had some familiarity. These models were analyzed to tabulate their attributes; screen capture software used and the resultant videos were analyzed to determine modeling procedure and time usage. Specifically, time usage was split into four categories: doing, thinking, searching, and waiting. Pre- and post- modeling interviews were also conducted and analyzed to determine if the exercises resulted in the manifestation of behaviors associated with adaptive expertise.

Analysis of the screen capture data showed that contextual exercises participants spent a greater percentage of the modeling time doing modeling activities than the control group. For the control group, a greater percentage of time was spent thinking. The analysis of interview data showed that the contextual group had more manifestations of behaviors associated with adaptive expertise. While not all categories were statistically significant, this provides partial evidence that contextual exercises promote adaptive expertise behaviors. Several statistically significant correlations were found between survey data and model attributes as well as modeling procedure. One of the more significant was the positive correlation between interview adaptive expertise related behaviors and the percentage of time spent modeling.

The above conclusions should be assessed in light of the limitations of the presented work. Namely, a small sample of students was used to collect these data. Future work will attempt to increase the number of participants and include practicing engineers.

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