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Development of Adaptive Expertise in Engineering Undergraduates through Contextual Computer Aided Design Modeling Activities*

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To survive and thrive in today's fast-changing workplace, engineers will need to become adaptive experts. Undergraduate education can play a critical role in improving engineering students' adaptive skills that are important for their future productivity. This education must integrate practice and mastery of Adaptive Expertise (AE) dimensions in the engineering curriculum. In this study we investigated the role of various factors on the undergraduate engineering students' manifestation of AE through contextual Computer-Aided Design (CAD) exercises. A total of 390 students from two universities were asked to model either a stylized or familiar component that they brought from home as a contextual exercise. In both cases, we conducted pre and post interviews with the students to capture how they approached their tasks and overcame any challenges. Effects of the contextualized activity on students' AE characteristics were investigated. In addition, utilizing the Adaptive Expertise Survey (AES), we collected data from over 600 participants spanning students over three years from two institutions as well as industry professionals. We found that the overall manifestation of AE during CAD exercises was significantly correlated with overall total AES scores. Participants' increased experience and education were shown to be associated with their increased AE captured through both the survey administrations and interview sessions. Contextual CAD modeling exercises had an effect on AE manifestations. Our findings provide insights into the research conducted to enhance CAD instruction. We report that multiple perspectives, goals and beliefs, and metacognitive skills are indicators of developing AE and that educators should consider promoting those skills in CAD education.

Keywords: CAD; adaptive expertise; contextual learning

1. Introduction

Today's engineering graduate will enter a workforce that is rapidly changing and adapting; from the "gig" economy to new business models, their careers will likely involve adapting to these changes. To be innovative, lifelong learners requires that they be able to adapt their expertise [1, 2]. In several fields, students have to be prepared to use modern computer-aided design (CAD) tools. A student who is not knowledgeable in using CAD tools will be unable to succeed in the coming model-based enterprise [3]. CAD tools allow engineers to turn ideas and design intent into digital artifacts that allow for analysis and production. Proper communication of design intent is critical in CAD modeling [4]. Design is at the core of engineering education [5]. Swiftly changing industries and CAD platforms demand engineering curricula to educate students so that their skills are transferable to other problems in the field.

Unfortunately, most current CAD instruction is focused on teaching declarative knowledge – the steps necessary to perform certain tasks in specific software platforms [6]. However, it is strategic or procedural knowledge that can be adapted to new situations or tasks [7]. Atman, et al. [8] find that even when students "know" something, they may not apply it appropriately in new situations; their expertise is not adaptable. The National Academy of Engineering report about how to educate the engineer of the future suggests a better alignment between what engineering students are taught and what they will be faced with in industry [9]. The CAD expertise students develop at the undergraduate level should be adaptive in nature and be extendable to engineering design in general.

To achieve the goal of sustainable productivity, it

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is essential to promote Adaptive Expertise (AE) in engineering education. Wineburg [10] defines AE as: "the ability to apply, adapt, and otherwise stretch knowledge so that it addresses new situations – often situations in which key knowledge is lacking". Brophy, et al. [1] define the interaction of efficient and innovative uses of knowledge as AE. Van Der Heijden [11] defines AE as the flexible or growth dimension of expertise. Better understanding AE skills and the activities that promote AE will allow students to transfer their knowledge to novel situations in a creative, innovative, and efficient way. This will produce more adaptive and effective engineers prepared for challenging and dynamic careers in industry and academia. As noted in a review of expertise [12], the learner, the task, and the environment call all affect AE and its manifestations. Understanding these factors can promote better educational and extracurricular activities to enhance AE.

In light of the above-mentioned issues and the related literature; our purpose in this study was to investigate the role of various factors on the manifestation of AE through contextual CAD exercises. We aimed at capturing students' AE characteristics while they were using a CAD tool through examining a contextualized activity. The effect of the contextualized activity on students' AE characteristics was investigated. We scrutinized which AE characteristics were revealed during the pre and post exercise interviews. Next, we compared the results with a survey that presents students' AES scores. In addition, the effect of differences in AE manifestation between students completed different CAD activities (stylized vs contextualized) was assessed. The role of student seniority (e.g., freshman versus upperclassmen) was assessed as it was a comparison between practicing engineers and students as well. The two main research questions we asked in this work are as follows:

- What were the effects of the contextualized CAD exercises on students' AE manifestations?
- What were the relations between engineering students' seniority and their observable AE characteristics?
- What were the relations between the AE characteristics of engineering students' and engineers in industry?

To answer the three research questions; we explored how the factors contributed to differences in the AE behaviors of students. To understand students' AE characteristics and how they might have developed, we designed and delivered CAD exercises augmented with contextual activities. We documented the revealed AE characteristics during the pre and post CAD exercise interviews and compared them to a survey that tabulated students' AE survey scores along with demographic information and professional experiences.

2. Background

In the present study, we examined the role of various factors on the manifestation of AE. These can be broadly defined as those related to the learning environment, the learner, and activities [12]. In the next section, we define and summarize previous work in the area of AE, the aspects of AE, and the factors that can lead to or inhibit the manifestation of AE.

2.1 Adaptive Expertise

AE is the term that defines capabilities of both being innovative and adaptive to new challenges while also having content knowledge associated with expertise [13]. The key to expertise is the mastery of concepts that allow for deep understanding of that information, transforming it from a set of facts into usable knowledge. The ability to process information quickly and recognize related solutions to problems in a particular area and/or domain of knowledge is known as expertise. Hatano and Inagaki [14] defined two types of expertise to make the distinction clearer: "routine expertise" and "adaptive expertise". Adaptive experts are those who perform procedural skills efficiently and understand the meaning of the skills and nature of their object. Routine experts simply learn to perform a skill faster and more accurately, without constructing conceptual knowledge, and can even perform a task through automation of the procedure. The fluency of finding related solutions to problems only makes students "routine" experts for specific problems. However, routine expertise does not mean students have flexible knowledge that may be needed to invent new ways to solve familiar problems and innovative skills to identify new problems [1]. While the development of routine expertise is valuable in usual settings, novel problem solving based on innovative aspects of the learning context and students' characteristics is necessary for efficient instruction. AE is the term that captures innovation and adaptivity along with expertise [13].

Individuals with adaptive expertise acquire the skills to solve novel problems. Because the medical profession is constantly changing and is seen as a field that requires adaptive expertise to be able to deal with these novel problems [15]; some worthy examples of the differences between routine and adaptive experts are medical diagnosis (e.g., [16, 17]). Raufaste, et al. [16] studied the adaptiveness of radiologists at different levels of experience in examining radiology scans. They evaluated participants from different levels of expertise: novices, intermediates, basic experts, and super experts. Participants interpreted x-rays that indicated 4 possible correct diagnoses but had several misleading clues. Results showed that novices and basic experts listed the fewest correct diagnoses, while super experts listed the most. These results as are interpreted as indicating a qualitative difference between the experiences of basic and super experts (similar to routine and adaptive experts). The basic experts had learned to efficiently determine the most likely diagnosis, but missed subtler possibilities. The basic and super experts had equal knowledge (though the super experts had more years of experience); the super experts were medical school faculty members. These experiences seem likely to develop the aptitudes and abilities that routine experts lack – flexibility, metacognition, and pursuit of extended learning experiences and challenging situations.

There have been several instruments developed to measure adaptive expertise; Bohle Carbonell, et al. [18] assess several. They note that the instruments developed by Van Der Heijden [11] and Fisher and Peterson [19] best conceptualize adaptive expertise. The Van Der Heijden [11] instrument includes five dimensions: knowledge, metacognition, sill requirements, social recognition, and growth and flexibility. The Fisher and Peterson [19] instrument includes four dimensions: multiple perspectives, metacognition, goals and beliefs, and epistemology. Ferguson et al. [20] propose an instrument with three dimensions: domain agility, self-assessed innovative practices, and orientation to innovation. Given its engineering focus, depth of background research for development, and initial validation, we used the Fisher and Peterson [19] instrument. Other work has used adapted versions [18, 21] of the Fisher and Peterson [19] instrument; preliminary work by the authors also used this instrument [22].

2.2 *Aspects of Adaptive Expertise*

Engineering design is often used to evaluate the effect of expertise on outcomes [8, 23–26]. While CAD tools are often part of the engineering design process, they are not the entirety of the process and in some cases can constrain design creativity [27, 28]; designers may only do what is available with the CAD tools that they know how to use. Creativity is one of the important aspects of AE [19]. Through an extensive literature review, Fisher and Peterson [19] identified four primary aspects of adaptive expertise (as mentioned above and detailed here): (a) multiple perspectives (MP), which is the ability to recognize situations where creativity is possible, (b) metacognitive self-assessment (MSA) referring to students' use of diverse techniques to self-assess and monitor their own understanding and performance, (c) goals and beliefs (GB) defining the views that students have concerning their learning goals and the nature of expertise, and (d) epistemology (EP) referring to how individuals perceive the nature of knowledge.

"Multiple perspectives" signifies the willingness of students to use a variety of representations and approaches when working on a problem [14]. This means students who have MP characteristic know that there may be more than one way to analyze, approach, and solve problems. In addition, they are open to new information and new ways of applying this information to the situations where creativity is possible [19]. These students can act flexibly in novel situations.

"Metacognitive self-assessment" characteristics help students monitor their problem solving, question limitations in their knowledge, and avoid simple interpretations of a problem [29]. People who have MSA ability can use various techniques to self-assess and monitor personal understanding and performance. They can use different representations and methods to solve a problem and can question their own understanding. Donovan, et al. [30] find that a "metacognitive" approach to teaching can help students learn to take charge of their own learning by defining learning goals and monitoring their progress in achieving them.

"Goals and Beliefs" defines the views that students have concerning their learning goals. Students who have GB for their learning view challenges as an opportunity for growth and are able to proceed in the face of uncertainty [19]. In addition, student beliefs about learning, motivation, and metacognition are all dimensions that focus on setting goals and working to achieve them [29]. According to Kalyuga [2], increased levels of learner control over learning tasks and selecting their learning goals are considered as an important condition for the development of metacognitive and self-regulation skills.

"Epistemology" is a metacognitive process; it is one's beliefs on knowledge, and attitudes towards the nature of the knowledge in the field, and its generation [31]. Students who demonstrate the EP attribute, perceive knowledge as an evolving entity rather than static; they realize the need to continually practice knowledge [19].

In order for students to develop these skills, it is important to create learning environments that support the development of cognitive, intrapersonal, and interpersonal competencies as a part of AE. Therefore, CAD activities introducing students to new challenges with contextual exercises rather than stylistic textbook exercises can examine if a student can effectively transfer skills to the new situation. Moreover, introducing students to new challenges in CAD modeling can help ensure CAD tools do not inhibit creativity and promote adaptive expertise characteristics.

2.3 Factors Affecting Adaptive Expertise

Learner characteristics can affect the manifestation of adaptive expertise. Younger students may show more marked gains from interventions designed to promote adaptive expertise [32]. However, more senior students tend to have more of the innovative and efficient behavior associated with adaptive expertise [26]. Intrinsic motivation and self-efficacy are also associated with increased adaptive expertise [33].

The learning environment can also influence the manifestation of adaptive expertise. The majority of engineering education has traditionally been focused on content; however, problem-based learning, namely the process, is more aligned with adaptive expertise [34]. Pierrakos, et al. [35] also show that a principles-based capstone course is more likely to produce adaptive expertise behaviors than a traditional lecture course. There are also examples from math, that show focus on content is detrimental to the development of adaptive expertise [36]. Martin [37] also shows that a more inquiry-based (problem-based, case-based, authentic) environment leads to improved adaptive expertise as opposed to a lecture-based one. Task variety has been shown as important for developing adaptive expertise [18]. The How People Learn Framework has been shown to improve the manifestation of adaptive expertise [38]. This framework states that an ideal learning environment includes characteristics of knowledge, learner, assessment, and community centeredness. Learner-centeredness characteristic emphasize exploring students' prior knowledge and interest and building the learning activity that properly addresses students' content understanding trajectory and personal interest. This personal interest provides the student with contextual learning opportunities.

2.4 Contextual Learner-centered Exercises

Contextual learning emphasizes problem solving and the need for education to take place in multiple contexts. This helps students become self-regulated and apply knowledge to the contexts of their lives [39]. Students learn more effectively when the activity they engage in has a personal meaning to them [40]. In a CAD instructional context, a contextualized activity can include designing a product that has direct connections to the students' daily life activities or their personal interest. When designing during a contextual exercise, it is important to ask if the task involve problems that require the students to use their knowledge creatively to find a solution and if the exercise is an engaging learning experience [41]. The CAD exercise presented in this work is incorporates these contextual learning principles.

According to Rogoff and Gardner [42], scaffolding within a contextual learning activity is effective in guiding the transfer of knowledge and skills from more familiar contexts, so assisting the learner to make connections within the context of the activity. Contextual Learning is based on a constructivist theory of teaching and learning that argues that humans generate knowledge and meaning from an interaction between their experiences and their ideas [43]. According to contextual learning theory, learning occurs only when students process new information or knowledge in such a way that it makes sense to them in their own frames of reference (their own inner worlds of memory and experiences) [44]. Contextualized learning could be used to encourage learners to adapt different levels of uncertainty, and to make decisions about adaptive plans and responses through the use of diverse reasonable scenarios [45].

Learning science research has documented the positive impact of learner-centered instructional strategies and contextual exercises on students' cognitive and affective domains [40]. Learner-centered characteristics highlight discovering students' prior knowledge and interest and constructing the learning activity that properly addresses students' content understanding trajectory and personal interest. Curriculum and instruction designed to nurture AE characteristics by engaging students in real-life problems can provide an important model of successful learning [40]. Bodnar, et al. [46] present a case showing the benefits of an experiential learning activity related to tissue engineering in developing adaptive expertise. Hatano and Oura [47] noted "while basic schools cannot make students real experts, they can place students on a trajectory towards expertise or prepare them for future learning" (p. 28).

3. Methods

3.1 Participants and Data Collection

The initial stage of this work consisted of collecting data using the Fisher and Peterson [19] adaptive expertise survey (AES) from students at Texas A&M University (TAMU) and Prairie View A&M University (PVAMU) as well as from industry professionals. The primary data for the CAD portion of the work were collected from different groups of students enrolled in CAD courses at the same two universities. A total 606 students and 23 industry professionals completed the AES. A total

Table 1. Demographic Breakdown of Participants

	PVAMU		**TAMU**		**Practicing Engineers**
	Overall	**CAD**	**Overall**	**CAD**	
Male	183	109	333	163	23
Female	37	20	53	12	0
Average Age (St. Dev)	21.6 (3.4)	20.3 (2.9)	21.4 (3.8)	22.3 (3.9)	45.1 (11.3)
Engineering Experience	20.9%	11.6%	35.8%	44.0%	N/A
Technical Experience	25.9%	20.2%	44.8%	54.9%	N/A

of 390 students participated in the CAD modeling activities. The CAD course at PVAMU comprised mostly freshman-level students, while the course at TAMU comprised junior and senior level students. The demographic breakdown for participants in the CAD modeling portion of the work is shown in Table 1.

3.2 Adaptive Expertise Survey (AES) and Demographic Data

The Fisher and Peterson [19] AES is a 42 items 6-point Likert-scale. All students and industry participants completed the AES and a demographic questionnaire designed by the authors. Demographic questionnaire items were designed to capture the students' and engineer participants' gender and age. For students, it also asked their year in school (e.g., sophomore), major, and experience. The students were asked if they had participated in a professional work experience (e.g., co-op, internship) and if they had technical experience (e.g., undergraduate research, working in a machine shop) [48]. Industry participants were asked their highest degree (doctorate, masters, bachelors) and their years of industry experience.

As noted, the AES includes four main constructs of AE: MSA, GB, EP, and MP. The survey was designed to assess the participants' beliefs and cognition in relation to the constructs of AE. The reliability of the scale was computed with Cronbach's alphas. The Cronbach's alpha of the survey was 0.795 (N=629), which indicated that the survey was a reliable instrument. MSA dimension had the highest reliability coefficient (α = 0.747) while the GB dimension had the lowest reliability coefficient (α = 0.507). MP (α = 0.602) and EP (α = 0.614) sub-dimensions were acceptably reliable.

3.3 Contextual Exercise

At both TAMU and PVAMU students were divided into alternative groups where they were asked to complete a CAD modeling exercise. The instructors used a previous graded exercise to ensure that the skill distribution of the various groups was even. One group was asked to complete the modeling of a stylized component that did not have any significant function. The stylized component either took the form of a drawing or a 3D printed plastic model of the component. These were considered the "control" situation and are analogous to the types of activities that students learning CAD traditionally engage in. Examples of the stylized model based on an exercise from [49] are shown in Fig. 1.

For the contextualized activity, the goal was to give students a novel activity that they have never done before. We asked students to bring an item from home that had similar characteristics as those of the analogous stylized component (i.e., geo-

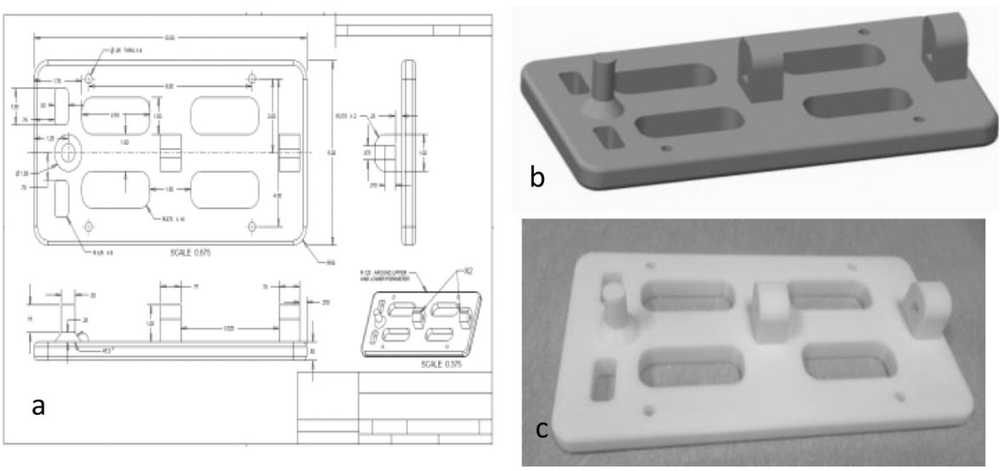

Fig. 1. Stylized Objects – a. Two-dimensional drawing; b. CAD rendering; c. 3D Printed Model.

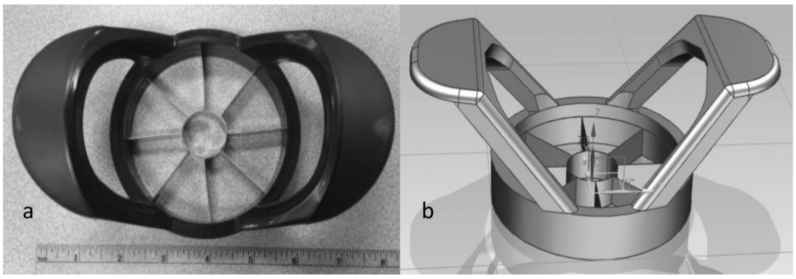

Fig. 2. Apple Slicer Modeled by a Student for the Contextual CAD Exercise – a. Physical Object; b. CAD Rendering.

metric complexity and composition). An attempt was made to create a new challenge for students where they could apply their existing knowledge. Fig. 2 provides an example of an object selected by a student and the associated CAD model for the contextual exercise.

In each case, students were given up to 75 minutes to complete the modeling of their object. This was a graded exercise, so students had an incentive to complete the modeling accurately. It should be noted that not all of the students completed the modeling exercise for either the contextual or stylized case. For instance, of the 175 TAMU students that engaged in the CAD modeling portion, only 116 completed their models.

3.4 Interviews and Code Extraction

We interviewed the participants before and after their modeling exercises. In the pre-activity interviews, we asked participants to discuss their modeling strategies along with what they expected from the exercise. In the post-activity interviews, we asked the participants to highlight any challenges they faced and how they attempted to overcome those challenges. Each interview lasted around 8–12 minutes (total pre and post). The interviews were audio recorded and transcribed verbatim. The pre and post interview questions (and associated follow-up questions) are shown in Table 2.

The transcripts of the interviews were analyzed using the constant comparative method [50, 51]. First open and axial coding strategies were used to analyze the interview responses. Next selective coding was used. The responses were coded along the four dimensions of adaptive expertise defined by [19]: multiple perspectives, metacognition, goals and beliefs, and epistemology. The coding and associated characteristics and adaptive expertise aspects are shown in Table 3. Pre- and post-interview instances for each dimension were tabulated and used to quantify an overall pre-, post-, and total interview AE manifestation counts. These AE manifestation counts were then compared to student AES data.

4. Analyses and Results

4.1 Group Differences – Quantitative Survey Data

The results from the individual constructs of the AES along with the overall adaptive expertise scores are shown in Table 4. As mentioned pre-

Table 2. Pre- and Post-modeling Activity Questions

Pre-modeling Activity Questions	
Question 1	What are the things you consider first when you are asked to model an object? • Why?
Question 2	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?
Question 3	Are you familiar with the object you are going to model today?
Question 4	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?
Post-modeling Activity Questions	
Question 1	The things you considered before you began modeling the object, were they helpful to you in the process? • How and why?
Question 2	What challenges did you encounter during the modeling process? • How did you overcome the challenges you faced during the modeling process?
Question 3	Was knowing the object or being familiar with it, helpful to you in your modeling process? • How and why?
Question 4	How confident are you in your model?

Table 3. Interview Data Coding and Associated Adaptive Expertise Dimensions

AE Dimensions	AE Associated Aspects	Codes from Interviews
Multiple Perspectives	Efficiency	Most efficient way to model Easiest way to model
	Innovation	
	Flexibility in novel situations	Creating drawing of object
Metacognition	Confidence	
	Successfully monitor one's own understanding	Have to pay close attention while modeling Have a good starting point Having a 3D part in hand helps
	Recognize that one's 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 & Beliefs	Seek out opportunities for new learning	Try learn better (if you had problems)
	Self-regulation strategies	Have an approach Have a way to organize the 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

viously, the majority of the students at PVAMU were freshmen, while the majority of those at TAMU were juniors. The ANOVA results in Table 5 show that there were statistically significant differences between groups for all constructs with the exception of the metacognition. Results that are statistically significant at the $p < 0.05$ are bolded.

The Scheffe Post Hoc results for the differences between the subgroups are presented in Table 6. There are statistically significant group differences for the multiple perspectives and epistemology constructs, as well as the overall adaptive expertise that follow the same group differences. In each of those cases, the differences between the PVAMU

Table 4. Descriptive Statistics for AES Data by Group

		N	*M*	*SD*	*Min*	*Max*
Multiple Perspectives	PVAMU	220	3.88	0.58	2.45	5.82
	TAMU	386	4.01	0.60	2.27	6.00
	Industry	23	4.29	0.47	3.45	5.45
	Total	629	3.97	0.60	2.27	6.00
Metacognition	PVAMU	220	4.36	0.63	2.67	6.00
	TAMU	386	4.40	0.58	1.78	6.00
	Industry	23	4.52	0.52	3.44	5.44
	Total	629	4.39	0.60	1.78	6.00
Goals and Beliefs	PVAMU	220	3.92	0.50	2.46	5.54
	TAMU	386	3.84	0.45	2.54	5.77
	Industry	23	4.12	0.29	3.62	4.69
	Total	629	3.88	0.47	2.46	5.77
Epistemology	PVAMU	220	4.13	0.57	2.33	5.56
	TAMU	386	4.45	0.51	2.89	5.89
	Industry	23	4.47	0.58	2.89	6.00
	Total	629	4.34	0.56	2.33	6.00
Total Adaptive Expertise	PVAMU	220	16.29	1.64	11.67	20.70
	TAMU	386	16.69	1.51	12.09	21.98
	Industry	23	17.40	1.29	14.39	19.79
	Total	629	16.58	1.57	11.67	21.98

Note: *N*: Number of participants; *M*: Mean; *SD*: Standard deviations.

Table 5. ANOVA Results for AES Data by Group

		SS	*df*	*MS*	*F*	*p*
Multiple Perspectives	Between Groups	4.71	2	2.352	6.726	**0.001***
	Within Groups	218.96	626	0.350		
	Total	223.66	628			
Metacognition	Between Groups	0.54	2	0.269	0.755	0.470
	Within Groups	223.29	626	0.357		
	Total	223.82	628			
Goals and Beliefs	Between Groups	2.32	2	1.158	5.347	**0.005***
	Within Groups	135.63	626	0.217		
	Total	137.94	628			
Epistemology	Between Groups	14.78	2	7.391	25.902	**0.000***
	Within Groups	178.62	626	0.285		
	Total	193.40	628			
Total Adaptive Expertise	Between Groups	38.57	2	19.285	8.039	**0.000***
	Within Groups	1501.71	626	2.399		
	Total	1540.28	628			

Note: *SS*: Sum of Squares. *df:* Degrees of Freedom *MS*: Mean Square. *F:* F distribution.
p: Probability of obtaining an F-ratio.

(more junior) students (J) and the TAMU or industry (I) participants are negative. There is no statistically significant difference for metacognition. In the case of goals and beliefs, the only statistically significant difference is between the TAMU and industry participants, which is negative.

4.2 Group Differences – Interview Data

As above mentioned, we interviewed the participants before and after the CAD modeling exercises to determine their modeling procedures and extract aspects related to adaptive expertise from the transcripts of the interviews. We counted the number of instances related with the various dimensions of adaptive expertise and tabulated them. We present the descriptive statistics for the post interviews and total instances in Tables 7 and 8, respectively.

The ANOVA results for post-exercise and total interview data are shown in Tables 9 and 10, respectively. These data show that there were statistically significant differences between groups for all aspects of adaptive expertise aspects mentioned in the interviews with the exception of epistemology. The Scheffe Post Hoc results for the differences between the subgroups for post-exercise and total interview data are shown in Tables 11 and 12, respectively. In the case of multiple perspectives, the industry participants had significantly more instances of adaptive expertise aspects in their

Table 6. Scheffe Post Hoc Multiple Comparisons for AES Data by Group

Dependent Variable			**Mean Difference (I-J)**	**Std. Error**	***P***
Multiple Perspectives	PVAMU	TAMU	–0.127	0.050	**0.040**
		Industry	–0.413	0.130	**0.007**
	TAMU	Industry	–0.286	0.127	0.080
Metacognition	PVAMU	TAMU	–0.033	0.050	0.809
		Industry	–0.153	0.131	0.504
	TAMU	Industry	–0.120	0.128	0.644
Goals and Beliefs	PVAMU	TAMU	0.081	0.039	0.121
		Industry	–0.200	0.102	0.148
	TAMU	Industry	–0.281	0.100	**0.020**
Epistemology	PVAMU	TAMU	–0.320	0.045	**<0.001**
		Industry	–0.345	0.117	**0.013**
	TAMU	Industry	–0.025	0.115	0.976
Total Adaptive Expertise	PVAMU	TAMU	–0.399	0.131	**0.010**
		Industry	–1.111	0.339	**0.005**
	TAMU	Industry	–0.712	0.332	0.102

Note: Std. Error: Standard Error.

Table 7. Post-Exercise Interview Adaptive Expertise Instance Data by Group

		N	*M*	*SD*	*Min*	*Max*
Post-exercise Interview Multiple Perspectives	PVAMU	93	0.54	0.69	0.00	3.00
	TAMU	139	0.72	0.82	0.00	4.00
	Industry	14	1.43	1.16	0.00	4.00
	Total	246	0.69	0.81	0.00	4.00
Post-exercise Interview Metacognition	PVAMU	93	0.56	0.68	0.00	3.00
	TAMU	139	0.81	0.92	0.00	4.00
	Industry	14	1.00	0.96	0.00	3.00
	Total	246	0.72	0.85	0.00	4.00
Post-exercise Interview Goals and Beliefs	PVAMU	93	0.43	0.71	0.00	3.00
	TAMU	139	0.91	0.95	0.00	5.00
	Industry	14	0.57	1.02	0.00	3.00
	Total	246	0.71	0.90	0.00	5.00
Post-exercise Interview Epistemology	PVAMU	93	0.13	0.45	0.00	3.00
	TAMU	139	0.10	0.37	0.00	2.00
	Industry	14	0.21	0.58	0.00	2.00
	Total	246	0.12	0.41	0.00	3.00
Post-exercise Interview Total Adaptive Expertise	PVAMU	93	1.66	1.36	0.00	6.00
	TAMU	139	2.54	1.79	0.00	11.00
	Industry	14	3.21	1.97	1.00	9.00
	Total	246	2.24	1.71	0.00	11.00

post-exercise interviews than either the PVAMU or TAMU students. While the post-exercise aspects of metacognition scaled with experience (fewest for PVAMU, most of industry), the differences between groups were not statistically significant. With respect to goals and beliefs, the only statistically significant difference was between PVAMU and TAMU students (who had the highest average number of instances). For overall post-exercise adaptive expertise aspects, we again see the most experienced participants (industry) exhibiting the greatest number of instances with the least experienced exhibiting the fewest. In both cases, the differences between the groups are statistically significant.

For the case of total adaptive expertise instances,

Table 8. Total Interview Adaptive Expertise Instance Data by Group

		N	*M*	*SD*	*Min*	*Max*
Post-exercise Interview Multiple Perspectives	PVAMU	93	1.34	1.29	0.00	5.00
	TAMU	139	1.89	1.67	0.00	9.00
	Industry	14	1.79	1.12	0.00	4.00
	Total	246	1.68	1.53	0.00	9.00
Post-exercise Interview Metacognition	PVAMU	93	1.48	1.20	0.00	5.00
	TAMU	139	1.94	1.48	0.00	7.00
	Industry	14	2.79	1.81	0.00	5.00
	Total	246	1.82	1.44	0.00	7.00
Post-exercise Interview Goals and Beliefs	PVAMU	93	1.38	1.73	0.00	7.00
	TAMU	139	2.71	2.03	0.00	10.00
	Industry	14	1.00	1.47	0.00	5.00
	Total	246	2.11	2.01	0.00	10.00
Post-exercise Interview Epistemology	PVAMU	93	0.72	1.04	0.00	5.00
	TAMU	139	0.68	0.88	0.00	4.00
	Industry	14	1.14	1.17	0.00	4.00
	Total	246	0.72	0.96	0.00	5.00
Post-exercise Interview Total Adaptive Expertise	PVAMU	93	4.92	2.83	0.00	14.00
	TAMU	139	7.23	4.05	0.00	24.00
	Industry	14	6.71	2.37	3.00	12.00
	Total	246	6.33	3.71	0.00	24.00

Table 9. ANOVA Results for Post-Exercise Interview Data by Group

		SS	*df*	*MS*	*F*	*p*
Post-exercise Interview Multiple Perspectives	Between Groups	9.916	2	4.958	7.895	**<0.001**
	Within Groups	152.604	243	0.628		
	Total	162.520	245			
Post-exercise Interview Metacognition	Between Groups	4.523	2	2.262	3.183	**0.043**
	Within Groups	172.680	243	0.711		
	Total	177.203	245			
Post-exercise Interview Goals and Beliefs	Between Groups	13.320	2	6.660	8.739	**<0.001**
	Within Groups	185.188	243	0.762		
	Total	198.508	245			
Post-exercise Interview Epistemology	Between Groups	0.183	2	0.091	0.536	0.586
	Within Groups	41.399	243	0.170		
	Total	41.581	245			
Post-exercise Interview Total Adaptive Expertise	Between Groups	57.487	2	28.744	10.585	**<0.001**
	Within Groups	659.879	243	2.716		
	Total	717.366	245			

Table 10. ANOVA Results for Total Exercise Interview Data by Group

		SS	*df*	*MS*	*F*	*p*
Post-exercise Interview Multiple Perspectives	Between Groups	16.902	2	8.451	3.715	**0.026**
	Within Groups	552.728	243	2.275		
	Total	569.630	245			
Post-exercise Interview Metacognition	Between Groups	25.646	2	12.823	6.503	**0.002**
	Within Groups	479.123	243	1.972		
	Total	504.768	245			
Post-exercise Interview Goals and Beliefs	Between Groups	117.719	2	58.860	16.472	**<0.001**
	Within Groups	868.317	243	3.573		
	Total	986.037	245			
Post-exercise Interview Epistemology	Between Groups	2.686	2	1.343	1.467	0.233
	Within Groups	222.517	243	0.916		
	Total	225.203	245			
Post-exercise Interview Total Adaptive Expertise	Between Groups	298.366	2	149.183	11.793	**<0.001**
	Within Groups	3073.963	243	12.650		
	Total	3372.329	245			

Table 11. Scheffe Post Hoc Multiple Comparisons for Post-Exercise Interview Data by Group

Dependent Variable			**Mean Difference (I-J)**	**Std. Error**	***P***
Multiple Perspectives	PVAMU	TAMU	–0.182	0.106	0.233
		Industry	–0.891	0.227	**<0.001**
	TAMU	Industry	–0.709	0.222	**0.007**
Metacognition	PVAMU	TAMU	–0.247	0.113	0.094
		Industry	–0.441	0.242	0.192
	TAMU	Industry	–0.194	0.236	0.714
Goals and Beliefs	PVAMU	TAMU	–0.484	0.117	**<0.001**
		Industry	–0.141	0.250	0.853
	TAMU	Industry	0.342	0.245	0.378
Epistemology	PVAMU	TAMU	0.028	0.055	0.877
		Industry	–0.085	0.118	0.772
	TAMU	Industry	–0.114	0.116	0.618
Total Adaptive Expertise	PVAMU	TAMU	–0.884	0.221	**<0.001**
		Industry	–1.558	0.472	**0.005**
	TAMU	Industry	–0.675	0.462	0.346

Table 12. Scheffe Post Hoc Multiple Comparisons for Total Exercise Interview Data by Group

Dependent Variable			**Mean Difference (I-J)**	**Std. Error**	***P***
Multiple Perspectives	PVAMU	TAMU	–0.548	0.202	**0.027**
		Industry	–0.442	0.432	0.594
	TAMU	Industry	0.106	0.423	0.969
Metacognition	PVAMU	TAMU	–0.459	0.188	**0.053**
		Industry	–1.302	0.403	**0.006**
	TAMU	Industry	–0.843	0.394	0.103
Goals and Beliefs	PVAMU	TAMU	–1.336	0.253	**<0.001**
		Industry	0.376	0.542	0.786
	TAMU	Industry	1.712	0.530	**0.006**
Epistemology	PVAMU	TAMU	0.037	0.128	0.959
		Industry	–0.422	0.274	0.307
	TAMU	Industry	–0.459	0.268	0.233
Total Adaptive Expertise	PVAMU	TAMU	–2.305	0.476	**<0.001**
		Industry	–1.790	1.020	0.216
	TAMU	Industry	0.516	0.997	0.875

again the ANOVA results show statistically significant difference between groups for all aspects with the exception of epistemology. For the total aspects of metacognition mentioned in the interviews, the PVAMU students' fewer instances (than TAMU students) were statistically significant. For overall interview data, the metacognition responses again scaled with expertise; however, in this case both mean differences between groups are statistically significant. For goals and beliefs, the TAMU students had statistically significantly higher instances of overall adaptive expertise instances in the interviews than either the PVAMU students or industry participants. For the overall instances of adaptive expertise, the only statistically significant difference was between PVAMU and TAMU students.

4.2.1 By Activity

As detailed in Section 3.3, students were split into groups to model either a stylized component (in drawing or three dimensional form) or participated in a contextualized activity. The contextualized activity presented students with a new challenge to apply their existing modeling knowledge. Participating students were interviewed prior to and after the exercise to assess their adaptive expertise

Table 13. Post-Exercise Interview Adaptive Expertise Instance Data by Exercise

		N	***M***	***SD***	***Min***	***Max***
Post-exercise Interview Multiple Perspectives	Contextual Model	110	0.63	0.68	0.00	2.00
	Stylized Drawing	93	0.56	0.76	0.00	3.00
	Stylized Model	29	1.00	1.04	0.00	4.00
	Total	232	0.65	0.77	0.00	4.00
Post-exercise Interview Metacognition	Contextual Model	110	0.77	0.87	0.00	4.00
	Stylized Drawing	93	0.65	0.78	0.00	3.00
	Stylized Model	29	0.66	0.94	0.00	3.00
	Total	232	0.71	0.84	0.00	4.00
Post-exercise Interview Goals and Beliefs	Contextual Model	110	0.54	0.76	0.00	4.00
	Stylized Drawing	93	0.69	0.87	0.00	3.00
	Stylized Model	29	1.52	1.02	0.00	5.00
	Total	232	0.72	0.89	0.00	5.00
Post-exercise Interview Epistemology	Contextual Model	110	0.15	0.47	0.00	3.00
	Stylized Drawing	93	0.08	0.30	0.00	2.00
	Stylized Model	29	0.07	0.37	0.00	2.00
	Total	232	0.11	0.40	0.00	3.00
Post-exercise Interview Total Adaptive Expertise	Contextual Model	110	2.09	1.41	0.00	6.00
	Stylized Drawing	93	1.97	1.71	0.00	6.00
	Stylized Model	29	3.24	2.17	1.00	11.00
	Total	232	2.19	1.68	0.00	11.00

Table 14. Total Interview Adaptive Expertise Instance Data by Exercise

		N	*M*	*SD*	*Min*	*Max*
Post-exercise Interview Multiple Perspectives	Contextual Model	110	1.57	1.31	0.00	5.00
	Stylized Drawing	93	1.57	1.71	0.00	9.00
	Stylized Model	29	2.38	1.70	0.00	8.00
	Total	232	1.67	1.55	0.00	9.00
Post-exercise Interview Metacognition	Contextual Model	110	1.63	1.20	0.00	6.00
	Stylized Drawing	93	1.92	1.56	0.00	7.00
	Stylized Model	29	1.72	1.51	0.00	6.00
	Total	232	1.76	1.39	0.00	7.00
Post-exercise Interview Goals and Beliefs	Contextual Model	110	1.89	1.84	0.00	10.00
	Stylized Drawing	93	2.04	2.09	0.00	7.00
	Stylized Model	29	3.69	1.83	0.00	9.00
	Total	232	2.18	2.02	0.00	10.00
Post-exercise Interview Epistemology	Contextual Model	110	0.72	0.84	0.00	4.00
	Stylized Drawing	93	0.67	0.99	0.00	5.00
	Stylized Model	29	0.72	1.16	0.00	4.00
	Total	232	0.70	0.94	0.00	5.00
Post-exercise Interview Total Adaptive Expertise	Contextual Model	110	5.81	2.93	0.00	14.00
	Stylized Drawing	93	6.20	4.28	0.00	23.00
	Stylized Model	29	8.52	4.26	4.00	24.00
	Total	232	6.31	3.78	0.00	24.00

using the process detailed above. The results are shown in Tables 13 and 14 for the post-exercise and total adaptive expertise, respectively; they are categorized by the type of modeling exercise that each participant engaged in.

The ANOVA results for post-exercise and total interview data by exercise type are shown in Tables 15 and 16, respectively. These analyses revealed that there are statistically significant differences between groups for multiple perspectives, goals and beliefs, and total adaptive expertise. This was the base for both the post-exercise and overall interview data.

The Scheffe post hoc comparisons provide additional insights. The stylized model had the greatest mean for the multiple perspectives aspect in both the post interview and total adaptive expertise. The difference was statistically significant when compared to the stylized drawing in the post-interview data and statistically significant for both the stylized drawing and the contextual model for the total interview data. In the case of goals and beliefs, the stylized model again had the greatest mean and the difference with the differences with the contextual model and the stylized drawing were statistically significant for both the post-interview and total cases. In the case of total adaptive expertise from the interviews the stylized model elicited more instances than either the contextual model or the

Table 15. ANOVA Results for Post-Exercise Interview Data by Exercise

		SS	*df*	*MS*	*F*	*p*
Post-exercise Interview Multiple Perspectives	Between Groups	4.374	2	2.187	3.776	**0.024**
	Within Groups	132.643	229	0.579		
	Total	137.017	231			
Post-exercise Interview Metacognition	Between Groups	0.909	2	0.454	0.638	0.529
	Within Groups	163.160	229	0.712		
	Total	164.069	231			
Post-exercise Interview Goals and Beliefs	Between Groups	22.236	2	11.118	15.663	**<0.001**
	Within Groups	162.553	229	0.710		
	Total	184.789	231			
Post-exercise Interview Epistemology	Between Groups	0.378	2	0.189	1.180	0.309
	Within Groups	36.708	229	0.160		
	Total	37.086	231			
Post-exercise Interview Total Adaptive Expertise	Between Groups	37.726	2	18.863	7.020	**0.001**
	Within Groups	615.304	229	2.687		
	Total	653.030	231			

Table 16. ANOVA Results for Total Exercise Interview Data by Exercise

		SS	*df*	*MS*	*F*	*p*
Post-exercise Interview Multiple Perspectives	Between Groups	16.562	2	8.281	3.534	**0.031**
	Within Groups	536.541	229	2.343		
	Total	553.103	231			
Post-exercise Interview Metacognition	Between Groups	4.498	2	2.249	1.160	0.315
	Within Groups	443.984	229	1.939		
	Total	448.483	231			
Post-exercise Interview Goals and Beliefs	Between Groups	77.029	2	38.514	10.223	**<0.001**
	Within Groups	862.726	229	3.767		
	Total	939.754	231			
Post-exercise Interview Epistemology	Between Groups	0.156	2	0.078	0.087	0.917
	Within Groups	204.723	229	0.894		
	Total	204.879	231			
Post-exercise Interview Total Adaptive Expertise	Between Groups	169.921	2	84.960	6.221	**0.002**
	Within Groups	3127.351	229	13.657		
	Total	3297.272	231			

Table 17. Scheffe Post Hoc Multiple Comparisons for Post-Exercise Interview Data by Exercise

Dependent Variable			**Mean Difference (I-J)**	**Std. Error**	***P***
Multiple Perspectives	Multiple Contextual Model	Stylized Drawing	0.068	0.107	0.817
		Stylized Model	–0.373	0.159	0.066
	Stylized Drawing	Stylized Model	–0.441	0.162	**0.026**
Multiple Metacognition	Contextual Model	Stylized Drawing	0.128	0.119	0.563
		Stylized Model	0.118	0.176	0.801
	Stylized Drawing	Stylized Model	–0.010	0.180	0.998
Multiple Goals and Beliefs	Contextual Model	Stylized Drawing	–0.152	0.119	0.443
		Stylized Model	–0.981	0.176	**<0.001**
	Stylized Drawing	Stylized Model	–0.829	0.179	**<0.001**
Multiple Epistemology	Contextual Model	Stylized Drawing	0.079	0.056	0.374
		Stylized Model	0.086	0.084	0.593
	Stylized Drawing	Stylized Model	0.006	0.085	0.997
Multiple Total Adaptive Expertise	Contextual Model	Stylized Drawing	0.123	0.231	0.867
		Stylized Model	–1.150	0.342	**0.004**
	Stylized Drawing	Stylized Model	–1.274	0.349	**0.002**

Table 18. Scheffe Post Hoc Multiple Comparisons for Total Exercise Interview Data by Exercise

Dependent Variable			**Mean Difference (I-J)**	**Std. Error**	***P***
Multiple Perspectives	Contextual Model	Stylized Drawing	0.003	0.216	1.000
		Stylized Model	–0.807	0.320	**0.043**
	Stylized Drawing	Stylized Model	–0.809	0.326	**0.047**
Metacognition	Contextual Model	Stylized Drawing	–0.297	0.196	0.318
		Stylized Model	–0.097	0.291	0.946
	Stylized Drawing	Stylized Model	0.201	0.296	0.795
Goals and Beliefs	Contextual Model	Stylized Drawing	–0.152	0.273	0.857
		Stylized Model	–1.799	0.405	**<0.001**
	Stylized Drawing	Stylized Model	–1.647	0.413	**<0.001**
Epistemology	Contextual Model	Stylized Drawing	0.052	0.133	0.928
		Stylized Model	–0.006	0.197	1.000
	Stylized Drawing	Stylized Model	–0.057	0.201	0.960
Total Adaptive Expertise	Contextual Model	Stylized Drawing	–0.395	0.521	0.750
		Stylized Model	–2.708	0.771	**0.002**
	Stylized Drawing	Stylized Model	–2.313	0.786	**0.014**

Table 19. Adaptive Expertise Survey and Total Exercise Interview Data Correlation

	2	3	4	5	6	7	8	9	10
1. Total Interview Multiple Perspectives	**0.251**	**0.328**	0.045	**0.697**	**0.151**	0.083	0.071	0.071	**0.134**
	<0.001	**<0.001**	0.481	**<0.001**	**0.018**	0.196	0.267	0.269	**0.036**
2. Total Interview Metacognition		**0.130**	**0.150**	**0.599**	0.087	0.051	–0.017	**0.129**	0.092
		0.041	**0.019**	**<0.001**	0.176	0.425	0.787	**0.044**	0.149
3. Total Interview Goals and Beliefs			0.009	0.728	-0.014	0.035	0.101	0.079	0.067
			0.882	<0.001	0.829	0.581	0.115	0.217	0.294
4. Total Interview Epistemology				**0.340**	0.091	0.027	0.09	0.036	0.084
				<0.001	0.155	0.67	0.162	0.572	0.189
5. Total Interview Total Adaptive Expertise					0.112	0.08	0.1	**0.131**	**0.149**
					0.081	0.212	0.118	**0.04**	**0.019**
6. AES Multiple Perspectives						0.398	0.341	0.324	0.750
						<0.001	<0.001	<0.001	<0.001
7. AES Metacognition							0.356	0.336	0.758
							<0.001	<0.001	<0.001
8. AES Goals and Beliefs								0.197	0.635
								<0.001	<0.001
9. AES Epistemology									0.664
									<0.001
10. AES Total Adaptive Expertise									

stylized drawing. These differences were statistically significant for both the post-interview and total exercise cases.

4.3 Interview and Survey Relationship

To investigate the relationship between the AES and the total manifestations of adaptive expertise behavior from the interviews, Pearson correlation was used to compare the results. These are shown in Table 19; the correlation is shown in the top of each cell with the significance below. While the interview and AES results are positively correlated for each aspect of adaptive expertise as well as total adaptive expertise, only multiple perspectives and total expertise are statistically significant.

5. Discussion

When examining the adaptive expertise survey (AES) data, it was expected that practicing engineer would have higher AE scores than their more junior student counterparts. This was generally the case. One-way ANOVA showed that with the exception of the metacognition aspect, there were statistically significant differences between groups. The post-hoc analysis did not show a statistically significant difference between the more senior students (TAMU) and the industry professionals for most aspects. However, there was a statistically significant difference for goals and beliefs. Significant industry practices (note the average age of the practicing engineers was over 45) may change ones views regarding opportunities for growth and the view of uncertainty. In other cases the differences were significant between the more junior students (mostly freshmen from PVAMU) and the TAMU students and industry professionals. This is in agreement with previous work showing the impact of education on adaptive expertise [26, 32].

One-way ANOVA were used to see if the groups were different from each other in terms of the AE manifestation during the interviews. For the differences between students who used different objects to model (3D stylized object, 2D stylized drawing, and 3D contextual object), it was expected that when students were given a novel challenge that they had not completed previously, they would respond to interview questions differently by means of the AE manifestation. Results indicated that in general, students who used a 3D printed stylized object to create a model in CAD had more AE manifestations than other groups.

Indeed, through the pre interview, exceptionally, students with 2D stylized drawing had more "metacognitive self-assessment" manifestations than students with a contextual 3D object. Here, it can be inferred that 3D objects were more challenging for students because they regularly worked with 2D drawings in the class. The 3D objects required them to take measurements and determine which features (modeling tools) could be used to create which geometric aspects. Although effortful problem solving in unfamiliar new situations requires metacognitive skills [2], in this study we observed that students who used 2D drawings expressed more of their metacognitive self-assessment skills comfortably before they started drawing. On the other hand, for the post interview; 3D stylized object students had more "multiple perspectives", "goals and beliefs" and more overall manifestation of AE behavior than students with 2D drawings. For the post interview, students were interviewed after their exercise and it can be interpreted that because 3D drawings were more challenging for students, they might have commented more on their performance and might have expressed more AE manifestations. In general, and unexpectedly, for both pre and post interviews, results indicated that students with 3D stylized objects had more overall manifestations of AE behavior than students with a 3D contextual object to model in CAD.

For the students, using a familiar object was a novel, more challenging situation. It was proposed that a novel problem would make students express more AE manifestation during the interviews; however, it did not. The reason why students working with familiar objects revealed less AE manifestation may be the students underestimated the complexity of modeling a familiar object and they might have believed that this process would be easier than they expected. They might have realized that their modeling plans did not work out like they assumed. Thus, during the interview, they did express less AE manifestations.

In addition, an assessment of any differences among students of different rank was undertaken. For both pre and post interviews, seniors have more "goals and beliefs" and more overall manifestation of adaptive expertise than freshmen. When the two campuses are compared, at TAMU where most students were seniors while at PVAMU, the students were mostly freshmen and sophomores; for all the observed statistically significant differences, students in TAMU reported higher AE scores than the students in PVAMU. As expected, students were more experienced with the modeling practice and their AE characteristics were enhanced. As noted above, this is an expected result, Fisher and Peterson [19] also found a similar patterns in their study. According to their findings, levels of adaptive expertise from freshmen to seniors to faculty increased monotonically. In addition, the average adaptive expertise score of engineering faculty was higher than that of the engineering freshmen. In another related work that used a design scenario to assess how undergraduates approach novel design challenges, Walker, et al. [26] concluded that fourth-year students created more efficient and innovative solutions than did first-year students. Fourth-year students were also more confident in their problem-solving abilities. Over time all students became more innovative and more confident as was observed in this study as well. As expected, much of the increase in innovation for beginning students emerged related to their experience and greater understanding of context.

It was expected that participants' AES scores would match with their reported AE characteristics in the interviews. The overall scores in AES and interviews are significantly correlated. When overall pre and post interviews total responses are compared with the AES scores, results indicate that students' manifestations during interviews are correlated with sub-dimension scores of AES. The multiple perspectives manifestation and the corresponding AES aspect have statistically significant correlations. The overall manifestations of adaptive expertise are significantly correlated with overall total AES scores.

The multiple perspectives characteristic is defined as openness to new information and novel ways to solve problems by recognizing opportunities for creativity [19]. More importantly, the students' overall sub-dimension of AES scores and overall manifestation of AE behavior in interviews are significantly correlated as expected. It can be concluded that, participants AES responses were consistent with their interview responses. These results provide insights to research conducted to enhance CAD instruction. These findings show that multiple perspectives, goals and beliefs, and metacognitive skills are good indicators of developing adaptive expertise and that educators should consider promoting those skills in CAD education.

According to Kalyuga [2] instructing for adaptive and flexible expertise requires developing advanced forms of skills that are applicable to a greater variety of situations. Integrating novel and challenging problems to classroom exercises will encourage students be more flexible, and adaptive. In a study on assessing AE, Pandy, et al. [38] find that challenge-based instruction can accelerate the trajectory of novice to expert development. With non-routine and creative exercises in classroom, essential attributes of adaptive expertise can be developed [2]. New challenges provide learners with additional contexts and develop their innovation skills which are necessary to manage the novel problems they will face after graduation, and potentially identify opportunities for new discovers [1]. In another study on the development of AE, Martin, et al. [52] claim that educators can and do help students develop adaptive expertise, even when students do not necessarily show such qualities initially. This can be achieved by using well-informed teaching methods that require students to engage in complex problem solving. Learning experiences that reflect both knowledge and novelty can increase the chances that people will develop adaptive expertise in their fields of interest [52].

6. Conclusion

The main purpose of this study was to investigate the role of various factors on the manifestation of AE through contextual CAD exercises. Findings confirmed the importance of practice for developing AE through engineering education by enhancing regular CAD exercises in the classroom. In fact, the results indicated that contextual CAD modeling exercises have an effect on AE manifestations during CAD exercises. The results will possibly bring insights for engineering educators to improve CAD instruction within undergraduate engineering education. As it is reported in the results, multiple perspectives, goals and beliefs, and metacognitive skills are significant indicators of developing AE in engineering education. Hence, it can be inferred that engineering educators should consider promoting those skills in their courses including CAD applications. For the future studies following this study, it is significant to explore and scrutinize the role of contextual exercise on students' manifestations of AE during CAD practices.

When we investigate the relationship between the AES and the total manifestations of AE behavior from the interviews; as expected the interview and AES results are positively correlated for each aspect of adaptive expertise as well as total adaptive expertise. In fact, this result in itself explains how important the use of contextual exercise in CAD practices.

To conclude; our study offers significant insights for engineering education and educational sciences researchers by means of improving engineering curriculum to develop AE in engineering education. The results confirm that contextual exercise in CAD practices can help advance students' goals & beliefs, multiple perspectives, metacognitive self-assessment and epistemology characteristics that are indicators of developing AE.

These outcomes also confirm the importance of practice to improve AE through engineering education by enriching regular CAD exercises in the classroom. With non-routine and creative exercises in CAD practice in engineering education, essential attributes of AE can be settled. Integrating original, challenging and contextual problems to engineering education exercises will encourage students be more flexible, and adaptive. Moreover, undergraduate engineering education should promote learning with problem based or related novel approaches that emphasizes students' efforts to solve complex daily life problems.

This study contributes to the literature as follows: (1) the results point to the importance of exploring the role of contextual exercise on students' expressions of AE manifestations; (2) it was observed that substituting a routine exercise with a challenging one can elicit a difference in students' AE behaviors; (3) the results provide evidence that AE is developed through the years and increases with experience.

This study has some limitations. AE in engineering education is a relatively recent topic in the literature. Therefore, more longitudinal work is required to be able to make definite claims about development of AE in engineering education. In addition, future research can explore what other possible exercises and practices contribute development of AE. Open questions still endure about how to gather the dimensions contributing development of AE when providing instruction to engineering students. Additionally, more in-depth and long-term studies specifying the nature of adaptive expertise should be conducted because on average, it takes approximately ten years of deliberate practice, along with the accumulation of experience to develop recognized levels of expertise. If this time frame is taken into consideration in the development of AE, this study and most studies in the literature focus mostly on relatively brief snap shots in time to observe development of AE. Therefore, in the future, the literature would benefit from studies that examine AE from a more longitudinal perspective with same participants. Examining AE over a more extended period of time could yield valuable insights.

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