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Investigating the Relationships Among Engineering Practitioners and Undergraduate Students' Adaptive Expertise Characteristics and Experiences*

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In this study, we explored the prospective and practicing engineers' adaptive expertise characteristics and documented the relations among their demographic information including gender, age, work experience, first-generation college student status, major, and education level. An Adaptive Expertise Survey (AES) and demographic questionnaires – designed by the researchers – were administered to collect data. A total of 606 participants, 23 of whom were practicing engineers, completed the Survey and demographic questionnaires. We conducted F-tests (ANOVA) to explore and document the relations among the participants' adaptive expertise characteristics and their demographics. The relations among the overall and sub-dimension scores of the AES and the participants' demographics were statistically significantly related. The more engineering experience the participants had, the more adaptive expertise characteristics they reported. Engineering undergraduates, who had technical employment and research experience related to engineering, had higher metacognitive self-assessment and overall dimension scores than the students who did not have any technical employment and research experience.

Keywords: adaptive expertise; engineering education; metacognition; epistemology

1. Introduction

To survive and thrive in today's swiftly-changing workplace and industry, engineering students will need to become adaptive experts. Their undergraduate education can play a critical role in improving the adaptive skills that are important for prospective engineers' future creativity and productivity. Undergraduate education must integrate practice and mastery of adaptive expertise (AE) dimensions in the engineering curriculum [1–6]. Most undergraduate engineering curricula aim at teaching skills and knowledge that are bounded by the discipline and within the limitations of the field's current epistemology and therefore students have difficulties to relate what they learn in their program with their practical applications [6]. Students are rarely being introduced to deal with challenges that require transfer of knowledge, metacognitive awareness, and epistemological thinking [7].

Research in science education suggests that it is critical to explore students' epistemological beliefs and compare and contrast them with the current epistemological beliefs in the field [8]. One reason that educators are interested in studying epistemological beliefs in science education has connotations with Kuhn's [9] ideas of how scientific knowledge is generated and operationalized. The researchers in science education are more aware of the dynamic and tentative characteristics of the scientific knowledge and consequently they are more concerned with the beliefs and skills their students have about how scientific knowledge is being generated and operationalized.

In engineering education, there are attempts to study students' epistemological beliefs and their metacognitive awareness, yet the literature is scarce. The term adaptive expertise has been coined and used to describe skills and knowledge that involve metacognitive awareness and personal epistemologies [10]. Adaptive expertise is defined differently from routine expertise where the transfer of knowledge from one domain to another is not necessarily an expectation [10].

Routine expertise that does not involve one's awareness of her own thinking and her beliefs

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about how the disciplinary knowledge is generated and operationalized in the field has been shown to be insufficient to develop a capacity to effectively address and solve ill-defined problems [10]. Adaptive expertise that involves metacognitive and epistemological awareness is pivotal for the prospective engineers to think creatively and be innovative in their practices when they come across novel and ill-defined engineering problems. To be an adaptive expert, learning experiences should promote being innovative and efficient to solve real-life problems and should include cooperative work with the industry so that prospective engineers can grow and develop simultaneously [11, 12, 2]. Adaptive experts tend to be more open to investigate and make use of their metacognitive and self-regulation skills, and to hold more advanced personal epistemologies. These characteristics make the adaptive experts flexible, innovative, and creative especially in novel situations [13]. Engineering is a field that is continually changing, so, it is important to train adaptive expert engineers to prepare them for this swiftly developing industry.

1.1 Study Purpose

The purpose of the present study was to explore the prospective and practicing engineers' adaptive expertise characteristics and document the relations among their demographic information including age, gender, work experience, first-generation college student status, major, and education level. A six point and 42 item Likert-scale instrument was used to measure adaptive expertise characteristics of the study participants. The instrument included four sub-dimensions: "multiple perspectives," "meta-cognitive self-assessment," "goals and beliefs," and "epistemology." The authors designed demographic questionnaires for the prospective engineers and practicing engineering. All participants completed both the adaptive expertise instrument and the demographic questionnaire. The data collected were analyzed to explore and document the relationships among the variables pertaining to participants' adaptive expertise and demographic characteristics.

2. Literature Review

2.1 Background: Adaptive Expertise Sub-dimensions

Fisher and Peterson [14] identified four main sub-dimensions that defined the adaptive expertise. These are (1) epistemology, (2) metacognition, (3) goals and beliefs, and (4) multiple perspectives.

2.1.1 Personal Epistemology

Adaptive experts frequently hold more sophisticated personal epistemologies [14]. Personal epistemology is defined as the beliefs and theories that individuals hold about knowledge and knowing [8]. Personal epistemology is one's beliefs on knowledge and attitudes towards the nature of the knowledge in the field and its generation. Adaptive experts believe that the knowledge in their field is dynamic in nature and it is subject to change as needed. They view the domain knowledge as not static or fixed, but fluid and changeable [10]. These beliefs allow the adaptive experts to be flexible to adapt the novel situations and to inquire or generate new knowledge instantaneously. Flexibility is an important aspect of being an adaptive expert [15]. However, flexibility is not a characteristic that experts can develop easily with routine practice. Mercier and Higgings [16] reported the difficulty of developing the flexibility characteristic of adaptive expertise. In their study, Mercier and Higgings [16] examined if a collaborative and multi-touch classroom supported the development of mathematical adaptive expertise, and specifically aspects of fluency and flexibility, when compared to a similar, individual task. A task that aimed to support both fluency and flexibility was developed and implemented in the collaborative and multi- touch classroom. In this experimental study, treatment group participants used a mathematical adaptive expertise application at a multi-touch laboratory, while the control group participants engaged in traditional and in-class discussions to complete the same activity. Both group participants completed a pre-test a week before the interventions. In the experimental group, the teacher based the class discussion around the patterns that the students had found on the tables, projecting the table content to the interactive whiteboard. In the control group, the teacher asked the students to identify the patterns they had created in their expressions. In the control group, the teacher attempted to replicate the discussion as closely as possible without the benefit of the shared display or collaborative activity to identify patterns. According to Mercier and Higgings' [16] results, students in both control and experimental groups increased in fluency after completing the activities, while students who were in the experimental group increased in fluency and flexibility of the expressions they created ($F(1, 84) = 31.01$ $p < 0.001$). Mercier and Higgings [16] concluded that while fluency could be developed with practice, designing activities that support the development of flexibility was more difficult.

2.1.2 Metacognition

Metacognition is an important characteristic of adaptive expertise [10]. The learner engages in self-monitoring and organization through "metacognition" that could be thought of a self-regulatory executive functioning keeping the learning process flowing smoothly [17]. Learners with metacognitive skills successfully monitor their own understanding. They recognize when their knowledge is incomplete [18, 14]. In addition, being capable of identifying (a) when additional information is required for understanding, (b) whether new information has been consistent with what they have already known, and (c) what correlations could be drawn that would improve their understanding are all metacognitive characteristics [10]. Metacognition plays a role in adaptive experts' ability to self-assess and judge when their current levels of understanding are not sufficient [19]. Metacognitive self-assessment is the ability to know when to select an efficient or an innovative procedure [20]. Metacognitive practice allows for learning to occur during the course of problem solving. Through metacognitive self-assessment characteristics, learners can actively engage with their own thinking and understanding and evaluate them in tandem.

2.1.3 Goals and Beliefs

The practitioners or learners having concerns for their learning often have some goals and beliefs for their learning and development. The practitioners and learners who are adaptive experts view challenges as learning opportunities and they seek out for those opportunities [14]. Those individuals employ self-regulation strategies that is another characteristic of adaptive experts. Self-regulation strategies help identify goals to generate ideas or improve an existing idea [21]. Adaptive experts also display the ability to transfer their knowledge, skills, beliefs, and attitudes to new situations. Pandy et al., [22] have defined the three important aspects of adaptive expertise as; (1) factual knowledge, which is one's ability to retain key facts and principles, (2) conceptual knowledge, which is one's ability to comprehend the underlying principles of the material taught as well as his or her quantitative skills, and (3) transfer, which is a one's ability to extend his or her knowledge to novel and unfamiliar situations.

2.1.4 Multiple Perspectives

For becoming an adaptive expert, it is important for a learner to have multiple perspectives that he or she should be able to look from different perspectives and should be able to use more than one way to analyze or solve problems [14]. In addition, with a fluent and flexible use of knowledge, a learner will be able to identify and expand on creative ideas; that is an important ability of holding adaptive expertise [15]. Martin et al. [23] suggested that if people experience substantial opportunities to engage in activities that promote the development of both knowledge and innovation, they can progress along a path to develop adaptive expertise. Innovation is the ability to consider a problem from multiple perspectives and the capability to escape from routine approaches [24]. Hatano and Inagaki [10] noted that certain individual characteristics, for example, being curious, influences the development of adaptive expertise. Confirming this, Bell, Horton, Blashki, & Seidel, [25] claimed that students who were to become adaptive experts must have retained motivation to solve problems through innovative ways. Innovation is one aspect of adaptive expertise, and it regulates skills necessary to identify what prior knowledge is needed to generate new ideas [21]. In an engineering education context, innovation is the ability to stop and consider a problem from multiple perspectives rather than barring on a more immediate and smaller set of possibilities [24]. To be an adaptive expert, efficiency should accompany innovation. Efficiency is a combination of consistency and accuracy, which are two other sub-dimensions of adaptive expertise [15, 24]. McKenna [21] defined efficiency as one's ability to fluently apply knowledge and skills. To meet novel challenges or problems of practice, adaptive experts respond flexibly to variable contexts and know how to constructively consider and account for multiple perspectives and potential solutions. Furthermore, adaptive experts modify their existing procedural skills or create new procedures [13].

3. Study Design

This study was funded by the National Science Foundation (NSF). The data were collected over four years. Student participants – the prospective engineers – were selected from Texas A&M University (TAMU) and Prairie View A&M University (PVAMU). Student participants were undergraduate students at the time of the data collection. Engineer participants – the practicing engineers – were selected from three different companies across the US. Between 2012 and 2016, 606 undergraduate students and 23 practicing engineers completed the study instruments. Undergraduate students completed a student demographic questionnaire developed by the researchers and the AES developed by Fisher and Peterson [14]. The student demographic questionnaire is in Appendix A. A similar demographic questionnaire for the practicing engineers (including questions about highest degree completed and years in service and excluding questions about first generation college student status and rank in school) was designed by the researchers and used to collect data from the engineers. The number of the study participants and their demographic information are summarized in Table 1.

3.1 *Adaptive Expertise Survey (AES) Reliability*

Fisher and Peterson [14] tested and reported the realibility and the validity of the AES in their study. We re-computed the realibility of the scale with the data we had collected. The Cronbach's alpha of the survey we computed was 0.795 (N = 630), which indicated that the survey was a reliable instrument. When we ran the reliability tests for the sub-dimensions of the survey, the "Metacognitive self-assessment (MSA)" dimension had the highest reliability coefficient (α = 0.747) while the "Goals and beliefs (GB)" dimension had the lowest reliability coefficient (α = 0.553). The "Multiple perspectives (MP)" (α = 0.602) and "Epistemology (E)" (α = 0.614) sub-dimensions were acceptably reliable.

4. Study Results

To examine the relations among the sub-dimensions of the Adaptive Expertise Scale (AES) and the study participants' demographic characteristics (i.e., gender, age, major, highest degree completed, years in service, professional work experience, technical employment or research experience, first generation college student status, and rank in school), F-tests (ANOVA) were run. Here we report only the statistically significant results.

4.1 *Differences with Respect to the Technical Employment or Research Experiences Related to Engineering (e.g., Machines Shops, Labs, Project Tasks, etc.)*

When we compared students (prospective engineers in other words) who had some technical employment or research experiences and those who did not have any technical employment or research experience, we observed that students who had some technical employment or research experiences related to engineering (e.g., machines shops, labs, project tasks, etc.) *(N = 195, M = 4.48, SD = 0.59)* had higher "metacognitive self-assessment (MSA)" sub-dimension scores in AES than students who did not have any technical employment/research experience *(N = 411, M = 4.33, SD = 0.60, F(1, 604) = 9.313, p = 0.002)*. Cohen's d was computed as 0.25 that showed a small to medium difference between the group means. Technical employment or research experienced students *(N = 195, M = 16.75, SD = 1.48)* had statistically significantly higher overall sub-dimensions scores than the inexperienced prospective engineers *(N = 411, M = 16.42, SD = 1.61, F (1, 599) = 6.451, p = 0.011)*

Table 1. Number of study participants and their demographics

		Sex		Age			Major		Professional Work Experience		Technical Emply/ Rsrch Experience		First Generation Status		Rank			
	N	Male	Female	18–22	23–30	30+	Mech. Eng.	Other	Yes	No	Yes	No	Yes	No	Fresman	Sophomore	Junior	Senior
TAMU students	386	333	53	234	41	7	266	80	109	150	138	248	NA	NA	76	15	71	223
PVAMU students	220	183	37	67	35	3	215	3	46	174	57	163	74	146	118	40	22	40
							Highest Degree		Years in Service									
							BS	Other	<5	>5, <10	= >10							
Engineers	23	23	0	0	1	22	23	0	1	4	18							
Total	629	539	90	301	77	32								Total*	194	55	93	263

* One missing value in rank.

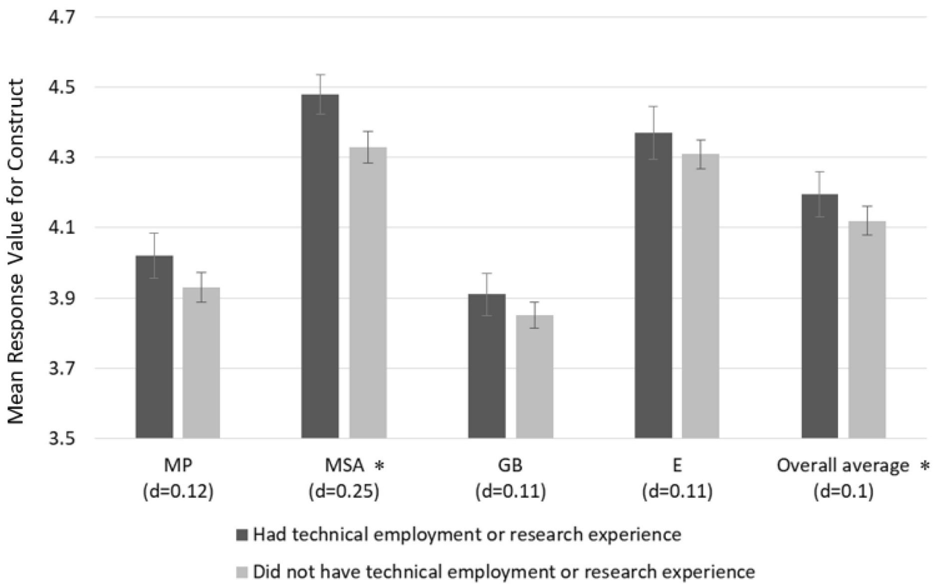

Fig. 1. Cohen's d effect size values and the means of students' responses to the AES items and its sub-dimensions (multiple perspectives, metacognitive self-assessment, goals & beliefs, epistemology). * The alpha value (*p*) was at 0.05.

at p = 0.05. Cohen's d was reported as 0.1 that showed a small difference between the group means. For the "multiple perspective (MP)," "goals and beliefs (GB)," and "epistemology (E)" perspectives, the differences were not statistically significant at $p < 0.05$. In Fig. 1, the means of the students' overall average AES scores and their AES sub dimension scores across their characteristics of having technical employment or research experiences related to engineering are presented. Cohen's d effect size [26] values are provided in parentheses under each group comparison.

4.2 Differences with Respect to Rank

When the relations among the students' rank and their AES responses were analyzed, we observed that the seniors *(N = 263, M = 4.05, SD = 0.56)* reported statistically significantly higher "multiple perspectives (MP)" sub-dimension scores in AES than the freshmen *(N = 194, M = 3.86, SD = 0.62, F(3, 601) = 4.091, p = 0.008)*. Cohen's d value was found as 0.33 that showed a small to medium group mean difference. Similarly, the seniors *(N = 258, M = 16.78, SD = 1.55)* reported statistically significantly higher overall sub-dimension scores in AES than freshmen *(N = 194, M = 16.28, SD = 1.47, F (3, 596) = 3.781, p = 0.01)* at the $p = 0.05$ level. Five senior students did not respond to all AES survey items and therefore their responses were excluded in the statistical analyses. For the "metacognitive self-assessment (MSA)" "goals and beliefs (GB)," and "epistemology (E)" sub-dimension scores, the differences were not statistically significant at $p < 0.05$. Cohen's d effect size was found as 0.08 between the freshman and senior students' overall sub-dimension scores, which showed a small group mean difference. In Fig. 2, the means of freshman and senior students' responses to the AES items and its sub dimensions are presented. The Cohen's d effect sizes are provided under each mean comparison.

4.3 Differences with Respect to School

When the two campuses and the practicing engineers were grouped into three categories and their responses to the AES items and it sub-dimensions were analyzed, we found that that the students in TAMU *(N = 386, M = 4.01, SD = 0.60)* reported statistically significantly higher "multiple perspectives (MP)" sub-dimension scores in AES than the students in PVAMU *(N = 220, M = 3.88, SD = 0.58, F(2, 626) = 6.73, p = 0.04)* at the $p = 0.05$ level. The Cohen's d effect size between the two group means was found as 0.22 which showed a small difference. Practicing engineers who worked in the industry *(N = 23, M = 4.29, SD = 0.47)* also reported statistically significantly higher "multiple perspectives (MP)" sub-dimension scores than the students in PVAMU *(N = 220, M = 3.88, SD = 0.58, F(2,626) = 6.73, p = 0.007)*. The Cohen's d effect size between the two group means was found as 0.78 that showed a large difference.

The students in TAMU *(N = 386, M = 4.45, SD = 0.51)* had statistically significantly higher "epistemology (E)" sub-dimension scores than the students in PVAMU *(N = 220, M = 4.13, SD = 0.57, F(2, 626) = 25.9, p = 0.000)*. Cohen's d effect size was reported as 0.59 that showed a medium to large group mean difference. Practicing engineers *(N =*

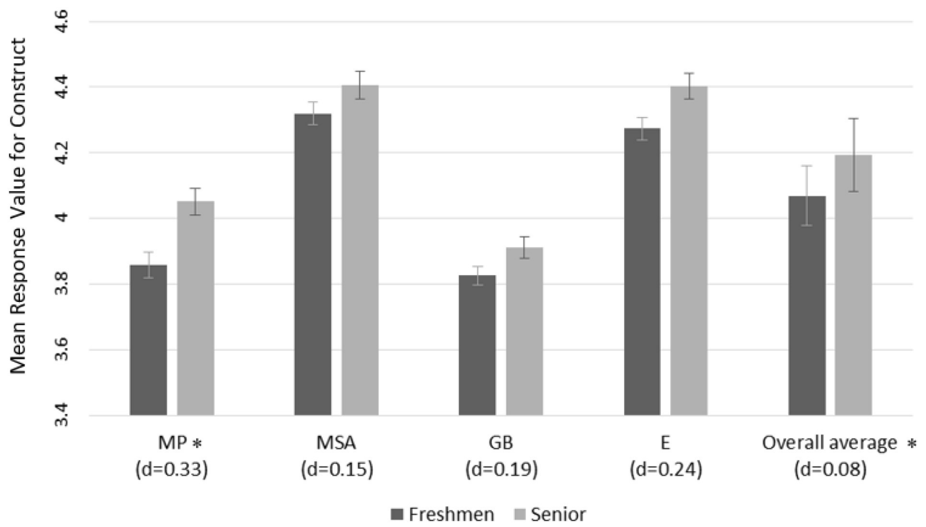

Fig. 2. Cohen's d effect size values and the means of freshmen and senior students' responses to the AES items and its sub-dimensions (multiple perspectives, metacognitive self-assessment, goals & beliefs, epistemology).
* The alpha value (p) was at 0.05.

23, M = 4.47, SD = 0.58) had statistically significantly higher "epistemology (E)" sub-dimension scores than the students in PVAMU *(N = 220, M = 4.13, SD = 0.57, F(2, 626) = 25.9, p = 0.013, Cohen's d = 0.6)* and the students in TAMU *(N = 386, M = 4.45, SD = 0.51, F(2, 626) = 25.90, p = 0.000, Cohen's d = 0.05)*.

For the "goals and believes (GB)" sub-dimension score, the practicing engineers *(N = 23, M = 4.11, SD = 0.29)* reported statistically significantly higher scores than the TAMU students *(N = 386, M = 3.84, SD = 0.45, F(2, 626) = 5.35, p = 0.02)*. Cohen's d effect size was computed as 0.74 that showed a large group mean difference. TAMU students' did not statistically significantly differ from PVAMU students when their responses to the "goals and believes (GB)" sub dimension items were compared.

In addition, the students in TAMU *(N = 381, M = 16.69, SD = 1.51)* had statistically significantly higher sub-dimension scores in AES than the students in PVAMU *(N = 220, M = 16.29, SD = 1.64, F(2, 621) = 8.01, p = 0.01)*. The Cohen's d effect size was computed as 0.06, that showed a small group mean difference. The practicing engineers *(N = 23, M = 17.40, SD =1.29)* had statistically significantly higher overall sub-dimension scores than the PVAMU students' scores *(N = 220, M = 16.29, SD = 1.64, F(2, 621) = 8.01, p = 0.005)*. Cohen's d was computed as 0.75 that showed a large group mean difference.

In Table 2, the means and the standard deviations of the practicing engineers' and TAMU versus PVAMU students' responses to the AES items and its sub dimensions are presented. Mean values that are statistically significantly different from one of the other means are marked with a star (*).

5. Discussion

For all statistically significant differences we observed in our data set, TAMU students and

Table 2. Means and standard deviations of the practicing engineers', TAMU students' and PVAMU students' responses to the AES items and its sub dimensions

	Practicing Engineering (N = 23)	**TAMU (N = 386)**	**PVAMU (N = 220)**
"Multiple perspectives (MP)" Mean Score (Standard Deviation)	4.29* (0.47)	4.01* (0.60)	3.88* (0.58)
"Epistemology (E)" Mean Score (Standard Deviation)	4.47* (0.58)	4.45* (0.51)	4.13* (0.57)
"Goals and believes (GB)" Mean Score (Standard Deviation)	4.11* (0.29)	3.84* (0.45)	3.92 (0.50)
"Metacognitive self assessment (MSA)" Mean Score (Standard Deviation)	4.52 (0.52)	4.40 (0.58)	4.36 (0.63)
Overall AES score Mean Score (Standard Deviation)	17.40* (1.29)	16.69* (1.51)	16.29 (1.64)

* Statistically significantly different at alpha value (p) < 0.05.

practicing engineers had higher "multiple perspectives (MP)," "epistemology (E)," and overall sub-dimension scores than PVAMU students. The practicing engineers had higher "multiple perspectives (MP)" and "epistemology (E)" scores than TAMU students as well. These results indicate that over time and through their undergraduate engineering education, the students gained some adaptive expertise characteristics. This finding is also reported and discussed in the literature pertaining to the development of adaptive expertise in undergraduate engineering education. Again, it should be noted that most of the TAMU students were seniors while those at PVAMU were freshmen.

Pierrakos et al. [3] conducted a quasi-experimental study and administered the AES [14] to measure their study participants' adaptive expertise characteristics. The AES was administered to two groups of students enrolled in two different sections of a senior design capstone course. One section was designated as experimental group and the other section was designated as control group. Experimental group students were taught using methods focusing on the principles of adaptive expertise. Control group students received traditional, lecture-based instructional method. In the experimental group, students were asked to work in collaboration and solve challenging design problems. They were encouraged to generate novel solutions. The results indicated that experimental group students' overall AES scores *($M = 17.13$, $SD = 1.53$)* were higher than the control group students' overall AES scores *($M = 15.93$, $SD = 1.72$)* and the difference was statistically significantly different at $p = 0.05$ level *($t\ (42) = 2.44$, $p = 0.019$, Cohen's $d = 0.74$)* [3].

Martin et al. [23] examined the development of adaptive expertise in the context of a bio-transport course in biomedical engineering. They designed multiple instruments with sub-dimensions to explore the changes in students' knowledge, adaptive expertise, attitudes, and believes. In efficiency dimension of the instruments, the items assessed participants' factual knowledge and ability to solve typical problems. In innovation dimension of the instruments, the items assessed participants' ability to apply their knowledge to reason through open-ended problems. Adaptive expertise related items required students to transfer their existing knowledge to a novel problem that was not directly taught in the course Martin et al. [23] modified the original AES and generated a version of it with items concerning four constructs of adaptive expertise (i.e., multiple perspectives, metacognition, goals and beliefs, and epistemology) [14]. Students completed the modified AES during the first and the last week of their course. Differences in students' responses over time were examined. Martin et al. [23] reported that students' knowledge, innovation, and adaptive expertise improved from the first exam to the third exam. The AES item scores remained stable across the semester, but students, who had higher scores on the first exam, had higher scores on the pre-AES as well. Students who had lower scores on the pre-AES revealed the greatest improvement on the adaptive expertise items from the first exam to the third exam emphasizing the potential for development of adaptiveness over time.

Walker et al., [24] investigated the concept of adaptive expertise in the context of an introductory engineering science course and a yearlong senior design course in biomedical engineering. They used a design scenario approach [27] to evaluate students' responses to an open-ended problem. Based on students' responses, they evaluated the quality of strategies students employed, the quality of students' questions, and students' confidence. Moreover, they categorized the quality of strategies students used under the efficiency dimension of adaptive expertise and the quality of students' questions under the innovation dimension. Their findings suggested that fourth-year students devised more efficient and innovative solutions than first-year students and over the course of one year all students became more confident in their approach.

Taylor, Peacock, Ko, and Rudolph [11] adapted a variation of challenge-based instruction for engineering design courses and they presented a challenging and open-ended real-life engineering design problem. In their study Taylor et al. expected to understand if design-based instruction increases adaptive expertise characteristics of engineering students. The authors concluded that with the challenging and open-ended problem based instruction, students' adaptive expertise characteristics positively evolved over time. In another study, Bodnar, Chritiani, Dahm, and Vernengo [2] explored the changes in adaptive expertise characteristics of engineering students through a challenging novel design task in an undergraduate tissue engineering laboratory course. Bodnar et al. [2] reported that their engineering student participants statistically significantly improved their adaptive expertise skills upon completion of an experiential learning activity at $p = 01$ level.

In summary, the literature presents a variety of empirical evidence that the engineering students' adaptive expertise skills and characteristics are improved when they engage in various learning experiences including cooperative work, self-regulation, and challenging problem solving strategies [4].

5.1 Limitations

Although most of our results were statistically significant, the number of practicing engineers *(N = 23)* is relatively small when compared to the number of engineering undergraduate student participants. Therefore, to be able to make a more precise comparison between the students and engineers, future work is required with a higher number of engineer participants that may allow for matching of sample characteristics between the students and engineers and for more representative samples. The practicing engineers that participated in this study spent a considerable amount of time to complete the data collection process. This might have resulted in the low number of practicing engineer participants.

6. Conclusion

The main purpose of this paper was to explore the relations between prospective and practicing engineers' adaptive expertise characteristics and their demographic information including gender, age, years in service, highest degree obtained, work experience, technical employment or research experience related to engineering, first-generation college student status, major, and rank in school.

Our analyses revealed that engineering undergraduate the students, who had technical employment or research experience related to engineering, had higher metacognitive self-assessment (MSA) and overall dimension scores than the students, who did not have any technical employment or research experience. As expected, with more technical employment or research experience, students' AE characteristics were enhanced.

When we analyzed students' AES responses with respect to their ranks in school, we found some differences that were statistically significant. When the students got more experience over the years in their undergraduate education, their adaptive expertise characteristics were enhanced. Senior students reported higher ASE scores than the incoming students that showed more developed characteristics towards adaptive expertise.

When we compared the two campuses, TAMU students reported higher adaptive expertise characteristics than PVAMU students as captured by the AES items. At first we taught this was because TAMU students had more advanced adaptive expertise characteristic than PVAMU students. However when we considered the covariances in the data set, we found that the difference between the two campuses was because of the students' ranks in their undergraduate education. In TAMU, most students were seniors, while in PVAMU, almost all students were freshmen and sophomores.

Our study provides insights for how to enhance engineering curriculum to develop adaptive expertise in engineering education through validating that employment and research experience at an undergraduate level can help improve students' metacognitive self-assessment and epistemology. Study findings show that metacognitive self-assessment and epistemology were good indicators of developing adaptive expertise. This suggests that; to improve engineering students' metacognition and epistemology, undergraduate engineering programs should promote or include cooperative work with the industry and basic research suitable for undergraduate engineering students.

In this study, significant results are presented, even though development of adaptive expertise in engineering education is a relatively new research topic. Our study compared the responses of a large group of participants to make inferences on their difference. Future studies, including longitudinal ones, are required to be able to make claims about the development (i.e., growth or change) of adaptive expertise. Future research can unpack what other characteristics contribute to developing adaptive expertise and what kind of exercises and practices will enhance students' adaptive expertise characteristics.

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References

1. X. Peng, P. McGary, E. Ozturk, Y. Bugrahan, M. Johnson and L. M. Valverde, Analyzing adaptive expertise and contextual exercise in computer-aided design, *Computer-Aided design and Applications,* **11**(5), pp. 37–41, 2014.
2. C. Bodnar, T. R. Christiani, K. Dahm and A. J. Vernengo, Implementation and assessment of an undergraduate tissue engineering laboratory course, *Education for Chemical Engineers*, **24**, pp. 52–59, 2018.
3. O. Pierrakos, R. D. Anderson and C. A. Welch, Measuring adaptive expertise in engineering education, in *American Society for Engineering Education*, New Orleans, LA, 2016.
4. L. Vanasupa, J. Stolk and T. Harding, Application of self-determination and self-regulation theories to course design: Planting the seeds for adaptive expertise, *International Journal of Engineering Education*, **26**(4), pp. 914–929, 2010.
5. B. R. Barbero, C. M. Pedrosa and G. C. Pena, The importance of adaptive expertise in CAD learning: maintaining design intent, *Journal of Engineering Design*, **29**(10), pp. 569–595, 2018.

6. R. G. B. De Araujo, M. V. A. Da Costa, B. Joseph and J. L. G. Sanchez, Developing professional and entrepreneurship skills of engineering students through problem-based learning: A case study in Brasil, *International Journal of Engineering Education*, **36**(1), pp. 155–169, 2020.
7. I. Fazey, Resilience and Higher Order Thinking, *Ecology and Society*, **15**(3), 2010.
8. B. K. Hofer, Epistemological Understanding as a Metacognitive Process, *Educational Psychologist*, **39**(1), pp. 43–45, 2004.
9. T. Kuhn, The Structure of Scientific Revolutions – with an Introductory Essay by Ian Hacking, Chicago: University of Chicago Press, 2012.
10. G. Hatano and K. Inagaki, Two Courses of Expertise, in *Child Development and Education in Japan*, New York, W.H. Freeman, pp. 262–272, 1986.
11. M. Taylor, S. B. Peacock, P. Ko and J. J. Rudolph, Changes in Teachers'Adaptive Expertise in an Engineering Professional Development Course, *Journal of Pre-College Engineering Education Research*, **5**(2), pp. 35–48, 2015.
12. D. L. Schwartz, J. D. Bransford and D. Sears, Efficiency and Innovation in Transfer, in *Transfer of Learning from a Modern Multidisciplinary Perspective*, Greenwich, CT, IAP, 2005.
13. G. Hatano and Y. Oura, Commentary: Reconceptualizing School Learning Using Insight from Expertise Research, *Educational Researcher,* **32**(8), pp. 26–29, 2003.
14. F. T. Fisher and P. L. Peterson, A Tool to Measure Adaptive Expertise in Biomedical Engineering Students, in *American Society of Engineering Education*, Albuquerque, NM, 2001.
15. S. Brophy, L. Hodge and J. D. Bransford, Adaptive Expertise: Beyond Apply Academic Knowledge, in *Annual Frontiers in Education*, Savannah, GA, 2004.
16. E. M. Mercier and S. E. Higgings, Collaborative Learning with Multi-Touch Technology: Developing Adaptive Expertise, *Learning and Instruction*, **25**, pp. 13–23, 2013.
17. R. Atkinson and L. Briggs, Contributions of Gagne and Briggs to a Prescriptive Model of Instruction, in *Instructional Design Theories and Models*, Hillsdale, NJ, Lewrence Erlbaum, 1983.
18. M. S. Donovan, J. D. Bransford and J. W. Pellegrino, How People Learn: Bridging Research and Practice, Washington, DC: National Academy Press, 1999.
19. J. D. Bransford, A. L. Brown and R. R. Cocking, How People Learn: Brain, Mind, Experience, and School: Expanded Edition, Washington, D.C.: National Academy Press, 2000.
20. V. M. Crawford, Adaptive Expertise as Knowledge Building in Science Teacher Problem Solving, in *Second European Cognitive Sciences Conference*, Delphi, Greece, 2007.
21. A. F. McKenna, An Investigation of Adaptive Expertise and Transfer of Design Process Knowledge, *Journal of Mechanical Design*, **129**(7), pp. 730–734, 2007.
22. M. G. Pandy, A. J. Petrosino, B. A. Austin and R. E. Barr, Assessing Adaptive Expertise in Undergraduate Biomechanics, *Journal of Engineering Education*, **93**(3), pp. 211–222, 2004.
23. T. Martin, A. J. Petrosino, S. Rivale and K. R. Diller, The Development of Adaptive Expertise in Biotransport, *New Directions for Teaching and Learning*, **108**, pp. 35–47, 2006.
24. J. M. T. Walker, D. S. Cordray, P. H. King and S. P. Brophy, Design Scenarios as an Assessment of Adaptive Expertise, *International Journal of Engineering Education,* **22**(3), pp. 645–651, 2006.
25. E. Bell, G. Horton, G. Blashki and B. M. Seidel, Climate Change: Could It Help Develop 'Adaptive Expertise'?, *Advances in Health Sciences Education,* **17**, pp. 211–224, 2012.
26. J. Cohen, A Power Primer, *Psychological Bulletin*, **112**(1), pp. 155–159, 1992.
27. F. McMartin, A. McKenna and K. Youseffi, Scenario Assignments as Assessment Tools for Undergraduate Engineering Education, *IEEE Transactions on Education*, **43**(2), pp. 111–119, 2000.
28. S. C. Scogin, C. Alexander, L. Gruenler, C. M. Mader and M. Bartoszek, Using authentic project-based learning in a first year lab to elevate students' perceptions of engineering, *International Journal of Engineering Education,* **36**(1(A)), pp. 186–200, 2020.

Appendix A – Prospective Engineer Demographic Questionnaire

Please answer the below questions by checking the appropriate boxes or filling in the necessary field:

1	Name – Last Name (write in)	____________________
2	Sex (check)	☐ Male ☐ Female
3	Age (write in)	☐
4	Rank/ level in college (check)	☐ Freshman ☐ Sophomore ☐ Junior ☐ Senior
5	Major (write in)	☐
6	Have you had a professional work experience related to engineering (e.g., internship, co-op, etc.)?	☐ Yes ☐ No
7	Have you had any technical employment or research experience related to engineering (e.g., machines shops, labs, project tasks, etc.)	☐ Yes ☐ No

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