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Establishing Baseline Measurements of Adaptive Expertise in First-Year STEM Students

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Abstract

Adaptive expertise is a construct developed to identify the cognitive skills involved in recognizing when and how to apply knowledge to successfully solve complex problems. The framework adopted for this study decomposes adaptive expertise into four distinct constructs: (1) multiple perspectives, (2) metacognition, (3) goals and beliefs, and (4) epistemology.

The aim of the study is to establish baseline measurements along the four dimensions of AE among various populations of first-year students in STEM. Specifically, we are interested in studying differences in adaptiveness between students with and without limited-income status. We are also interested in studying differences in adaptiveness between men and women.

From survey data collected from our incoming class over the past two years, preliminary results indicate that women score significantly higher than men in three dimensions (MP, META, and EPIST), but significantly lower than men in GB (goals and beliefs). Limited income students score lower than their non-LI counterparts in all AE dimensions, but significantly so in only two dimensions (MP and EPIST). Additional data collection is needed to understand how to interpret variations in scores and to establish baseline measurements with greater confidence.

Introduction

Problem solving is an essential skill in engineering. This skill requires more than simply memorizing information; the ability to understand when and how this knowledge should be applied is critical to solving problems successfully. The construct of *adaptive expertise* (AE) can be used to define the specific cognitive skills involved [1-2]. An adaptive expert can be described as an individual who can solve a novel problem by adapting and "stretching" their knowledge in new situations [3-4].

While the importance of adaptive expertise in engineering is generally agreed upon [5-8], there is some debate about how to characterize the multiple facets of adaptive expertise [1,9]. Specific attitudes and cognitive skills are often attributed to adaptive experts. In 2001, Fisher and Peterson [2] developed a model around attitudes toward continuous learning and epistemology, as well as metacognitive skills. Pierrakos et al. [8] proposed a modified version of the Fisher and Peterson model by adding the constructs of innovation and conceptual understanding, while Ferguson et al. [10] added self-efficacy and resilience. Bransford et al. [11] proposed an AE model where innovation and efficiency were two orthogonal dimensions, with novices at the lower end of both scales and adaptive experts at the higher end of both scales.

The framework adopted for this study is the original model by Fisher and Peterson [2], which decomposes adaptive expertise into four distinct constructs: (1) multiple perspectives, (2) metacognition, (3) goals and beliefs, and (4) epistemology. The "multiple perspectives" (MP) construct characterizes a willingness to use a variety of representations and approaches to analyze and solve problems. Metacognition (META) characterizes a self-awareness of one's own learning and level of comprehension. The “goals and beliefs” (GB) construct characterizes a willingness to embrace challenge as an opportunity for growth (growth mindset). Epistemology (EPIST) characterizes a recognition of knowledge as an evolving entity and the importance of continuous learning.

From this framework, a 42-item survey instrument was developed and validated to measure and track AE along the four dimensions defined above. Measuring AE levels across various populations, e.g. engineering students vs. working professionals, could provide insight into how adaptiveness progresses over time and eventually how targeted activities can be designed to develop these types of cognitive skills in our engineering students.

Currently there is very limited data on AE measurements of any population. In this study, we aim to establish baseline measurements of these dimensions by collecting and analyzing survey data from first-year students in STEM fields over multiple years. This research is conducted in conjunction with an NSF S-STEM program aimed to support our limited income students through scholarship, mentorship, and workshops centered around AE. Accordingly, we are specifically interested in studying differences in adaptiveness between students with and without limited-income status. We are also interested in studying differences in adaptiveness between men and women.

Methods

All first-year students at Stevens Institute of Technology are required to participate in subject pool activities as a part of their core humanities courses. Starting in Fall 2021, the adaptive expertise survey by Fisher and Peterson was offered as an option to fulfill this requirement. A total of n=645 participated in this survey in Fall 2021 and n=620 in Fall 2022. Only students in STEM majors are included in this study. Demographic information of the survey participants is provided in Table 1 below. As seen in Figure 1, the distribution of gender and income status of the survey participants from both years are similar.

Table 1. Demographic Information for Survey Participants

Year	n	Men	Women	Non-binary	Low Income	Non-Low Income
Fall 2022	620	382	221	17	94	526
Fall 2021	645	409	217	19	127	518

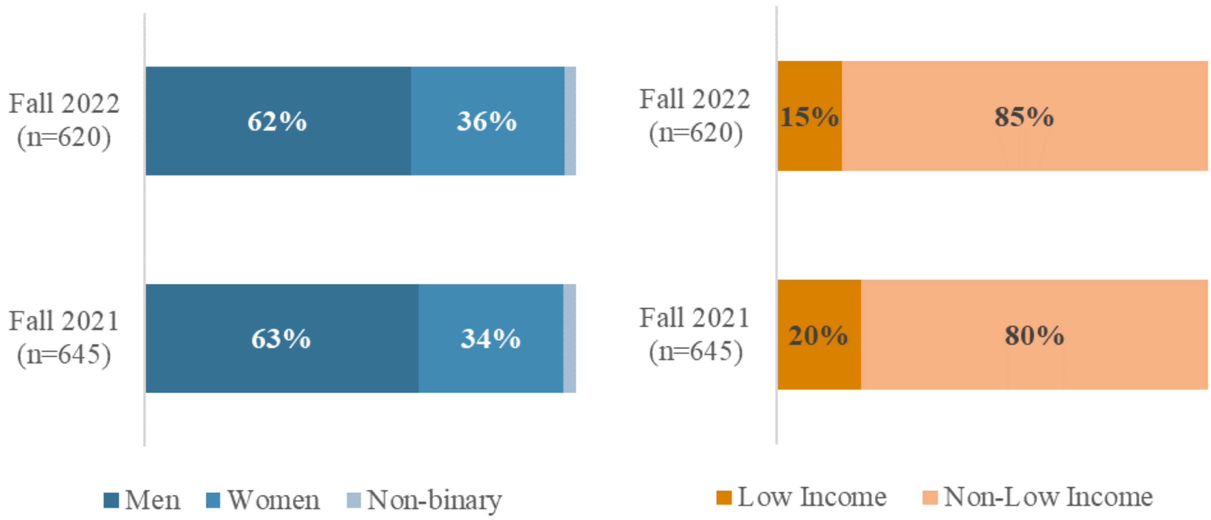

Figure 1. Gender breakdown (left) and income status breakdown (right) of survey participants from the F21 and F22 cohorts.

The full set of 42 survey questions is included as an appendix. Students are asked to respond to each question using a 6-point Likert scale ranging from 1 (strongly disagree) to 6 (strongly agree). Survey items are a mix of positively and negatively worded questions, which are then appropriately factored into the calculation of an average score along each of the four dimensions of adaptive expertise: (1) multiple perspectives – MP, (2) metacognition – META , (3) goals and beliefs – GB, and (4) epistemology – EPIST.

Results and Discussion

Average scores along each of the four AE dimensions are compared for incoming students in Fall 2021 (F2021) and Fall 2022 (F2022). Results are in a similar range to that of the Fisher and Peterson (FP) study, as seen in Figure 2 below. Similar trends in relative subscale scores are also observed across all three cohorts. In each cohort, students scored highest in the EPIST subscale and lowest in the MP and GB subscales. These consistencies between separate cohorts are promising for establishing baseline measurements for each subscale among first-year students.

A statistical analysis comparing the F2021 and F2022 cohorts, however, revealed that differences in average scores between the two cohorts were statistically significant along all AE subscales, except the GB subscale, as shown in Table 2. It is unclear what these differences could be attributed to, as the two cohorts are similar in demographic makeup (see Table 1) and academic background (all first-year STEM students). It is also difficult to make meaningful conclusions from just two data points; data from additional cohorts will be necessary to understand the typical range of variation in average scores along each subscale.

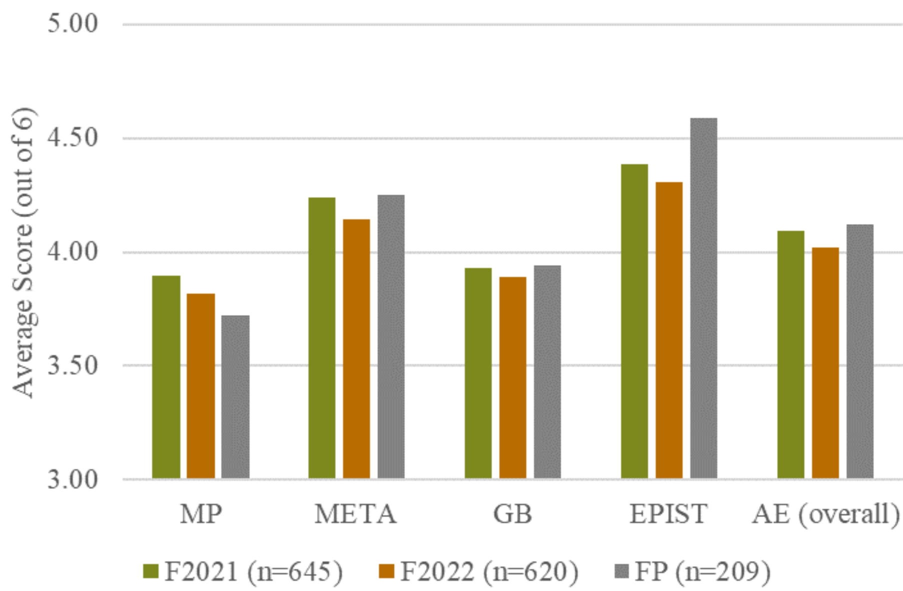

Figure 2. Average score in each AE subscale and overall AE score for incoming cohorts of Fall 2021 and Fall 2022 in this study, compared with first-year engineering students from the Fisher and Peterson (FP) study in spring 2000.

Table 2. Comparison of AE scores for the Fall 2021 and Fall 2022 cohorts

	F2021 (n=645)		**F2022 (n=620)**		**T-Test**	
	Mean	*SD*	*Mean*	*SD*	*t-value*	*p-value*
MP	3.898	0.544	3.816	0.540	2.690	0.007
META	4.240	0.597	4.145	0.592	2.816	0.005
GB	3.935	0.559	3.891	0.551	1.413	0.158
EPIST	4.383	0.597	4.308	0.620	2.179	0.029
AE (overall)	4.093	0.438	4.019	0.424	3.018	0.003

Differences in adaptiveness by gender

Average scores for men and women are shown in Table 3 and Figure 3 below. Due to the small sample size, non-binary student data are not shown here. In both first-year cohorts, significant differences were observed in three of the four subscales (MP, META, and EPIST), where women scored significantly higher than men. Women scored lower than men in the GB subscale in both cohorts, but this difference was significant for only the F2022 cohort.

We will continue to track whether women score significantly lower than men in this GB subscale with future cohorts, as this trend could have implications in targeting women with activities that develop and encourage a growth mindset.

Table 3. Comparison of AE scores for the Fall 2021 and Fall 2022 cohorts, by gender

Fall 2021	**Men (n=409)**		**Women (n=217)**		**T-Test**	
	Mean	*SD*	*Mean*	*SD*	*t-value*	*p-value*
MP	3.849	0.528	3.984	0.562	-2.971	0.003
META	4.185	0.597	4.335	0.588	-3.004	0.003
GB	3.959	0.583	3.878	0.505	1.726	0.085
EPIST	4.330	0.586	4.460	0.601	-2.618	0.009
AE (overall)	4.063	0.442	4.137	0.425	-2.016	0.044

Fall 2022	**Men (n=382)**		**Women (n=221)**		**T-Test**	
	Mean	*SD*	*Mean*	*SD*	*t-value*	*p-value*
MP	3.762	0.526	3.910	0.560	-3.243	0.001
META	4.086	0.572	4.240	0.613	-3.098	0.002
GB	3.939	0.557	3.805	0.525	2.918	0.004
EPIST	4.256	0.622	4.377	0.609	-2.326	0.020
AE (overall)	3.996	0.424	4.055	0.425	-1.651	0.099

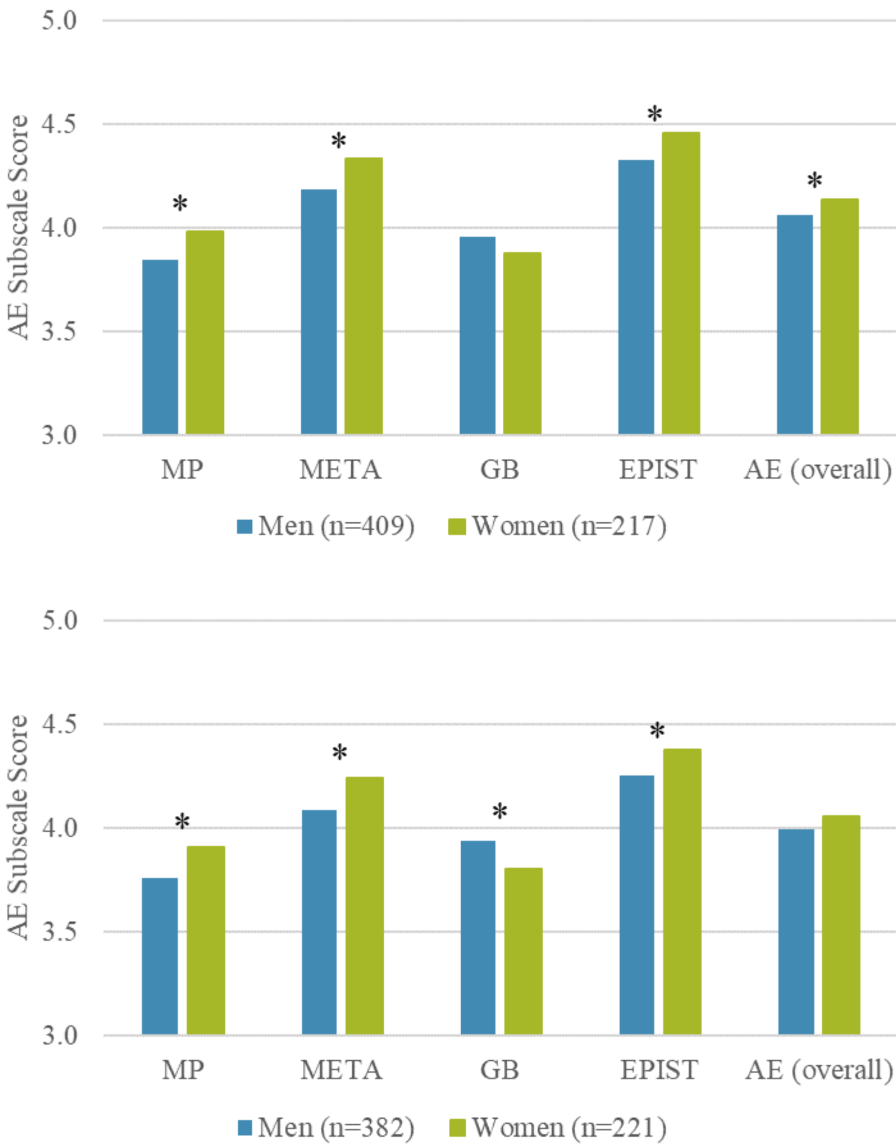

Figure 3. Average score in each AE subscale and overall AE score for men and women from the incoming cohorts of F2021 (top) and F2022 (bottom). Significant differences indicated with (*).

Differences in adaptiveness by income status

Average scores for each AE subscale are compared between low income (LI) students and non-LI students in Table 4 and Figure 4. The trends vary considerably between the two cohorts, F2021 and F2022. In the F2021 cohort, LI students scored lower in all AE subscales, but significantly lower in the MP and EPIST subscales, as well as overall AE score. In the F2022 cohort, however, no significant differences were observed in any AE subscale or overall AE score. In fact, LI students scored slightly higher in the MP and META subscales.

These seemingly contradictory results indicate that there may be large variation in the LI student population from year to year, and further analysis of the various backgrounds and sub-groups within this student population may be required to draw meaningful conclusions.

Table 4. Comparison of AE scores for the F2021 and F2022 cohorts, by income status

Fall 2021	**Low-Income (n=127)**		**Non-Low Income (n=518)**		**T-Test**	
	Mean	*SD*	*Mean*	*SD*	*t-value*	*p-value*
MP	3.818	0.489	3.918	0.554	-2.012	0.045
META	4.206	0.560	4.244	0.605	-0.683	0.495
GB	3.871	0.524	3.945	0.563	-1.400	0.163
EPIST	4.242	0.576	4.423	0.597	-3.146	0.002
AE (overall)	4.014	0.395	4.111	0.444	-2.413	0.017

Fall 2022	**Low-Income (n=94)**		**Non-Low Income (n=526)**		**T-Test**	
	Mean	*SD*	*Mean*	*SD*	*t-value*	*p-value*
MP	3.835	0.581	3.812	0.533	0.367	0.714
META	4.171	0.626	4.140	0.586	0.469	0.639
GB	3.853	0.606	3.897	0.541	-0.724	0.469
EPIST	4.217	0.600	4.324	0.622	-1.536	0.125
AE (overall)	3.998	0.454	4.023	0.419	-0.518	0.605

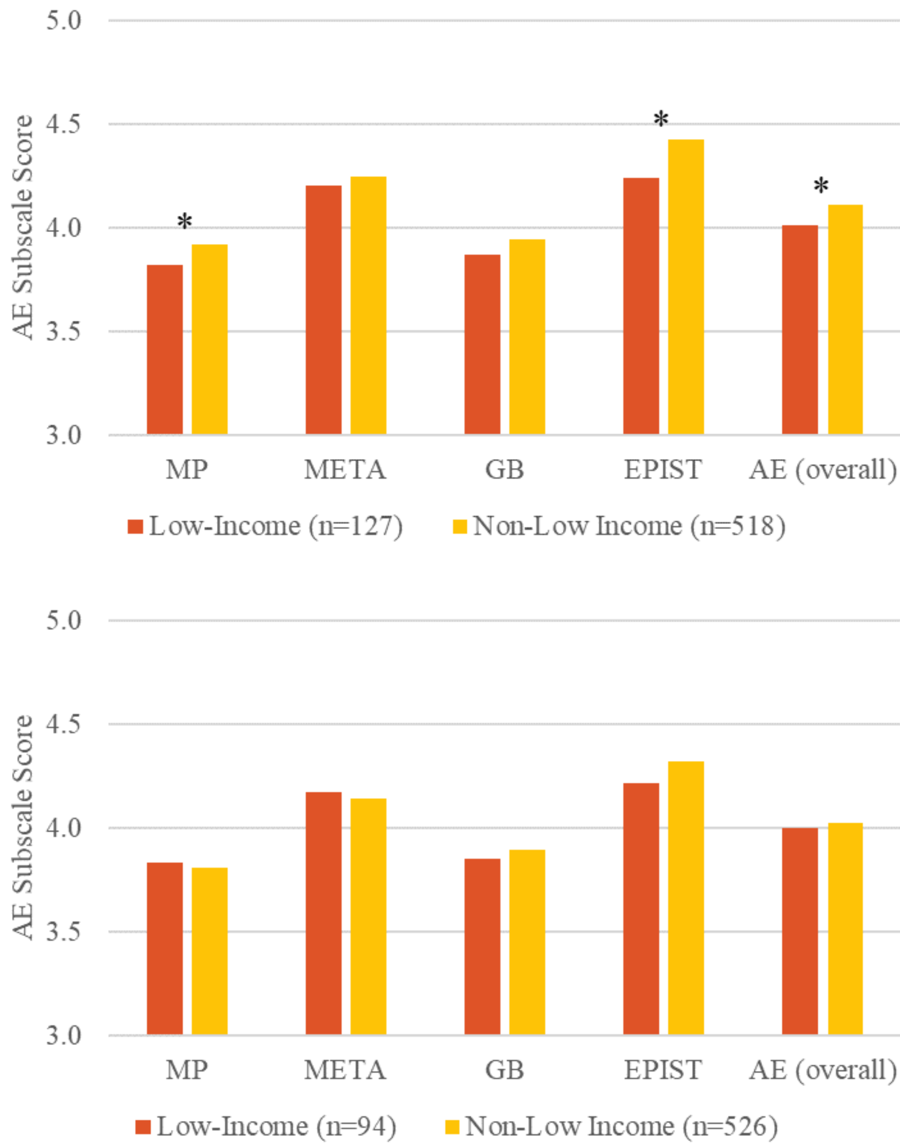

Figure 4. Average score in each AE subscale and overall AE score for low income (LI) and non-LI students from the incoming cohorts of F2021 (top) and F2022 (bottom). Significant differences are indicated with (*).

Conclusions and Future Work

Results from this study are being used to slowly build up sufficient data to establish baseline measurements of adaptive expertise among first-year students in STEM majors, with the broader goal of eventually understanding how adaptiveness progresses over time and how it can be cultivated in our students. Relative baseline measures between the four AE subscales are starting to take form, where average scores for the MP and GB subscales are consistently the lowest and average scores for the EPIST subscale are consistently the highest.

Additional work is needed in understanding the roles that gender and income status play on adaptiveness in STEM students. Women appear to outperform men in the MP, META, and EPIST subscales, but score lower in the GB subscale. No clear trend has emerged among low income and non-low income students in any of the four AE subscales. Because the results for these student groups varied considerably from one year to the other, this could indicate a need for further breakdown of the student groups or simply that there is a large variation of adaptiveness among the LI and non-LI groups.

Future work includes measuring adaptiveness in subsequent incoming cohorts, as well as tracking adaptiveness in students as they progress through the degree program. Tracking growth in the four AE dimensions as students move toward graduation will also be helpful with establishing baseline measurements.

Acknowledgements

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References

[1] Fisher, F. T., & De Rosa, A. J. (2021, April), A review of Adaptive Expertise and its integration within undergraduate engineering curricula Paper presented at Middle Atlantic ASEE Section Spring 2021 Conference, Virtual . 10.18260/1-2—36282

[2] Peterson, P., & Fisher, F. (2001, June), A Tool To Measure Adaptive Expertise In Biomedical Engineering Students Paper presented at 2001 Annual Conference, Albuquerque, New Mexico. 10.18260/1-2--9908

[3] Wineburg, S., Reading Abraham Lincoln: An expert/expert study in the interpretation of historical texts, *Cogn. Sci.*, vol. 22, no. 3, pp. 319–346, 1998, doi: 10.1207/s15516709cog2203_3.

[4] Hatano, G., & Inagaki, K. (1986). Two courses of expertise. In H. Stevenson, H. Azuma, & K. Hakuta (Eds.), Child development and education in Japan (pp. 262–272). New York: W. H. Freeman.

[5] Brophy. S., Hodge, L. & Bransford, J. (2004, October). Work in progress – Adaptive expertise: Beyond apply academic knowledge. In the ASEE/IEEE Frontiers in Education Conference.

[6] Martin, T., & Benton, T., & McKenna, W., & Ko, P. (2010, June), Transfer of Adaptive Expertise To Transform Engineering Education Paper presented at 2010 Annual Conference & Exposition, Louisville, Kentucky. 10.18260/1-2--16881

[7] Hicks, N.M., Bumbaco, A.E., & Douglas, E.P. (2014). Critical Thinking, Reflective Practice, and Adaptive Expertise in Engineering. 2014 ASEE Annual Conference & Exposition. June 15-18, Indianapolis, IN.

[8] Pierrakos, O., Anderson, R.D., & Welch, C.A. (2016), Measuring Adaptive Expertise in Engineering Education, 123rd ASEE Annual Conference & Exposition, New Orleans, LA

[9] Bohle Carbonell, K., Stalmeijer, R.E., Könings, K.D., Segers, M., & van Merriënboer, J. J. G. (2014). How Experts Deal with Novel Situations: A Review of Adaptive Expertise. Educational Research and Reviews, Vol. 12, pp.14–29.

[10] Ferguson, J.H., Lehmann, J., Zastavker, Y.V., Chang, S., Higginson, R.P., & Talgar, C.P. (2018). Adaptive Expertise: The Development of a Measurement Instrument. In Proceedings of the 125th ASEE Annual Conference & Exposition, June 24-27, Salt Lake City, UT.

[11] Bransford, J., Stevens, R., Schwartz, D., Meltzoff, A., Pea, R., Roschelle, J., Vye, N., Kuhl, P., Bell, P., Barron, B., Reeves, B., & Sabelli, N. (2006). Learning Theories and Education: Toward a Decade of Synergy, in P. A. Alexander & P. H. Winne (Eds.), Handbook of Educational Psychology, pp. 209–244. Lawrence Erlbaum Associates Publishers.

Appendix A. Fisher-Peterson Adaptive Expertise (AE) Survey (Fisher, 2001)

Survey administered using a six-point Likert scale with the order of items scrambled. Note that items marked (*) and in italics denote "negative" items where "strongly disagree" would correspond to the characteristics of an adaptive learner.

Table A1. Fisher-Peterson Adaptive Expertise (AE) Survey items grouped by construct.

Item	Survey Item
	Multiple Perspectives
1	I create several models of an engineering problem to see which one I like best.
2	When I consider a problem, I like to see how many different ways I can look at it.
*3**	*Usually there is one correct method in which to represent a problem.*
*4**	*I tend to focus on a particular model in which to solve a problem.*
5	I am open to changing my mind when confronted with an alternative viewpoint.
*6**	*I rarely consider other ideas after I have found the best answer.*
*7**	*I find additional ideas burdensome after I have found a way to solve the problem.*
8	For a new situation, I consider a variety of approaches until one emerges superior.
*9**	*I solve all related problems in the same manner.*
*10**	*When I solve a new problem, I always try to use the same approach.*
*11**	*There is one best way to approach a problem.*
	Metacognitive Self-Assessment
12	As I learn, I question my understanding of the new information.
13	I often try to monitor my understanding of the problem.
*14**	*As a student, I cannot evaluate my own understanding of new material.*
*15**	*I rarely monitor my own understanding while learning something new.*
16	When I know the material, I recognize areas where my understanding is incomplete.
*17**	*I have difficulty in determining how well I understand a topic.*
18	I monitor my performance on a task.
19	As I work, I ask myself how I am doing and seek out appropriate feedback.
*20**	*I seldom evaluate my performance on a task.*
	Goals & Beliefs
21	Challenge stimulates me.
*22**	*I feel uncomfortable when I cannot solve difficult problems.*
*23**	*I am afraid to try tasks that I do not think I will do well.*
*24**	*Although I hate to admit it, I would rather do well in a class than learn a lot.*
25	One can increase their level of expertise in any area if they are willing to try.
26	Expertise can be developed through hard work.
*27**	*To become an expert in engineering, you must have an innate talent for engineering.*
*28**	*Experts in engineering are born with a natural talent for their field.*
*29**	*Experts are born, not made.*
30	Even if frustrated when working on a difficult problem, I can push on.
*31**	*I feel uncomfortable when unsure if I am doing a problem the right way.*
32	Poorly completing a project is not a sign of a lack of intelligence.
*33**	*When I struggle, I wonder if I have the intelligence to succeed in engineering.*
	Epistemology
34	Knowledge that exists today may be replaced with a new understanding tomorrow.
35	Scientists are always revising their view of the world around them.
*36**	*Most knowledge that exists in the world today will not change.*
*37**	*Facts that are taught to me in class must be true.*
*38**	*Existing knowledge in the world seldom changes.*
39	Scientific theory slowly develops as ideas are analyzed and debated.
40	Scientific knowledge is developed by a community of researchers.
*41**	*Scientific knowledge is discovered by individuals.*
*42**	*Progress in science is due mainly to the work of sole individuals.*