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Measuring adaptive expertise amongst first-year STEM students

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Work in Progress: Measuring adaptive expertise amongst first-year STEM students

Abstract

Engineering programs must weave coverage of disciplinary content with the ability of students to apply and extend this content knowledge to new contexts and for use in their professional practice as engineers. It is, therefore, necessary for schools to promote and cultivate additional dispositions within their students that better enable them to adapt and employ their disciplinary knowledge. The concept of an "adaptive expert" (AE) has been previously developed within the learning sciences to describe an individual with deep content knowledge but who also displays additional cognitive characteristics that better enable them to employ their knowledge and skills in practice. Four constructs have been identified in the literature as forming the basis of this adaptive expertise: 1) multiple perspectives (MP), 2) metacognition (META), 3) goals and beliefs (GB), and 4) epistemology (EPIST).

Upon entry to an engineering program, it is likely that students will present with different levels of development and awareness within these particular dimensions. Baseline levels must, therefore, be measured in order to assess these levels of development and before research-based practices and activities can be designed to promote growth in these constructs. In this work-in-progress study, the "adaptiveness" of incoming undergraduate STEM students (n=711) is measured using a previously developed validated survey instrument used in other studies to measure levels of adaptive expertise amongst undergraduate students by determining their levels along the four identified dimensions of AE.

Based on this survey data, statistically significant differences were found in the AE constructs for men and women, with women outscoring men in three of the four AE subscales (MP, META, EPIST) and men outscoring women in goals and beliefs (GB). White students were found to score statistically higher than Asian students in both multiple perspectives (MP) and goals and beliefs (GB), while no statistically significant differences were observed when White and Black/African American students were compared. The mean epistemology (EPIST) scores for White, non-Hispanic students was statistically higher than Hispanic students, with low-income students scoring lower than non-low-income students on this subscale.

This project seeks to provide baseline data concerning the adaptivity of incoming first-year students. A structured mentoring program focusing on elements of AE will then be implemented and student growth in the dimensions of AE assessed through their program of study.

Introduction

STEM graduates are increasingly asked to work in broader, interdisciplinary fields that require application of their technical expertise across ever more diverse contexts. The ASEE, NAE, and various other organizations have all cited the need for engineers and STEM professionals of the future to be “T-shaped professionals” who have deep understanding of their discipline but an ability to apply their knowledge and skills more broadly [1]–[3]. As such, STEM education programs are increasingly interested in not only producing subject matter experts, but also graduates who can apply this knowledge. In this context, the term “adaptive expertise” (AE) has been used to describe certain dispositions that should be fostered in students if they are to meet these criteria [4], [5].

The term “expertise” is often used to define a person with the deep content knowledge necessary to operate effectively in a given field [6]. Experts typically have: (1) knowledge that is greater than memorized facts or operations related to the field; (2) an ability to notice important patterns and features that is obscure to novices; (3) an organized knowledge structure reflecting their deep understanding, and (4) the ability to quickly and accurately retrieve their knowledge with low cognitive effort. It is understood, however, that experts in the same discipline may exhibit these characteristics to different degrees or differ in the manner in which they are able to apply this expertise in practice [7], [8].

Developed in the field of learning science, the term “adaptive expert(ise)” (AE) or “adaptiveness” was developed to describe this difference in the manner in which experts apply their expertise [7], [8]. A seminal study on this topic [8] describes the difference in how two historians approach and interpret a rare historical text. It was observed that a historian with prior knowledge of the topic approached the problem from a perspective grounded in their existing knowledge, sometimes at the expense of utilizing a fresh approach. The second historian, whose experience was more general, employed far different approaches to interpreting the text, in particular employing the scientific method to a much greater degree. Wineburg described this historian as demonstrating “the ability to apply, adapt, and otherwise stretch knowledge” so that they could effectively utilize their expertise in a new situation [8]. In this example, the second historian would be described as an adaptive expert, someone with the ability to apply and expand their knowledge to new contexts as compared to a more routine expert (e.g., the first historian).

A framework that allows for the measurement of adaptive expertise was defined by Fisher and Peterson in 2001 [5]. This framework was developed for use in the biomedical engineering field from a (contemporary) review of the literature surrounding AE and identified four constructs that described AE: (1) multiple perspectives, (2) metacognition, (3) goals and beliefs, and (4) epistemology. These constructs are further characterized in Figure 1 and in more detail in the original paper [5]. In the AE definition developed by Fisher and Peterson, care was taken by the authors to describe AE differently to other dispositions described in the field such as creativity or self-confidence. The authors describe AE as a cognitive approach, or way of thinking that determines how one approaches problem solving in a given context. More specific characteristics such as self-confidence or creativity are not considered in this definition as while someone with higher levels of AE might be expected to display greater levels of these dispositions, being creative or self-confident (for example) is not required to approach a problem in a manner consistent with the definition of AE. Using this definition of AE, Fisher & Peterson then developed and validated a 42-item survey instrument that could be used to measure AE, with the goal of using this instrument to track student growth along the four dimensions they believed characterized an adaptive expert.

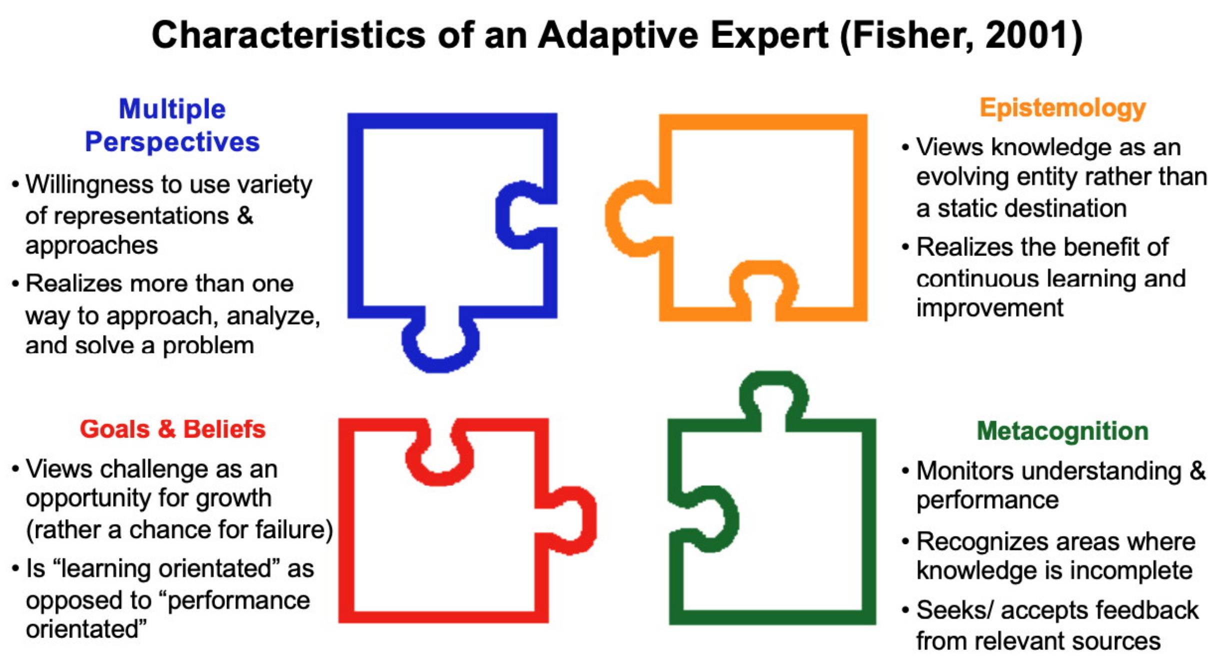

Figure 1. Four constructs describing the characteristics of an adaptive expert (adapted from Fisher & Peterson, 2001[5]).

More recently, several authors in engineering [9]–[11] have developed a slightly modified (and broader) definition of Adaptive Expertise which adds innovation and problem solving efficiency through the use of a model in which "an adaptive expert is not simply the next level above a routine expert in a linear progression but instead a completely different type of expert" [11]. Various groups have then used this model to try to teach and assess AE via the use of problem-based learning and student ability to solve "novel problems" [12]–[15]. In addition, the original work of Fisher and Peterson was further developed by Ferguson et al. [16] who chose to reduce the length of the AE survey as well as to alter the focus of the survey to three alternative dimensions: domain agility, self-assessed innovative practice, and orientation to innovation. This survey was then delivered to a large population of students to assess the impact of co-operative work experiences on student growth. In line with this variation in the field, a recent review of the literature surrounding the use of the term AE in engineering found no consistent definition [4], as clearly there remain different interpretations as to the manner in which the community views and defines AE.

In this study, the original survey of Fisher and Peterson (see Appendix A) [5] will be used to generate baseline AE data for the incoming cohort of first-year undergraduate students at Stevens Institute of Technology. This data will then be used to track student growth and development in AE throughout their course of study. The survey of Fisher & Peterson was chosen as the AE measurement instrument based on our agreement with Fisher & Peterson's understanding of adaptive expertise as "*a disposition or mindset with which individuals may approach problems within a specific domain*" rather than something more related to innovation or the various other constructs described in the literature. Additionally, as we plan to use this survey to assess STEM students of multiple majors throughout their course of study, the exclusion of domain-based knowledge as a component of AE is important - individuals may be adaptive and employ adaptive approaches to problem solving without displaying strong content knowledge and thus, we can consider the adaptiveness of students at various levels of education as they progress within their program.

Methodology and Survey Details

At Stevens, all first-year students are required to complete a number of subject pool activities as part of their common humanities course requirements. For those who decline or wish to opt out of a specific assignment, there are alternative assignments available. In Fall 2021, an adaptive expertise survey based on that described by Fisher & Peterson (see Appendix 1 for survey items) [5] was offered as one of the options towards receiving this credit. A total of n=711, first-year, typically first semester, incoming students responded to the survey. The breakdown of the survey population is given in Table 1 in terms of gender and race. Students were able to select more than one racial or ethnic identity. Only those listing a single identity are listed in the table, however, as sample sizes of other groups were small. Both positively and negatively worded items were included in the AE survey (as previously validated by Fisher & Peterson) and students responded to the questions using a 6-point Likert scale ranging from 1 (strongly disagree) to 6 (strongly agree). For positively worded items a score of 6 would indicate that a given participant was strongly disposed towards the given construct of adaptive expertise being measured, while a score of 1 would indicate the opposite.

Table 1: Breakdown of survey participants

Student Group	Population (n)
Total number of respondents	711
STEM major	647
Non-STEM major	64
Men	454
Women	249
Non-binary	8
White	466
Asian	154
Black / African American	22
White non-hispanic	392
Spanish, Hispanic or Latino	113

Results

The following data are provided in terms of mean survey scores along the four dimensions (subscales) of the AE framework as defined by Fisher & Peterson [5]: (1) multiple perspectives (MP), (2) metacognition (META), (3) goals and beliefs (GB), and (4) epistemology (EPIST). While 711 students participated in the survey, data presented here deal with smaller subsets of this population with groups composing smaller numbers oftentimes omitted due to the low sample sizes. Although students were able to select multiple racial categories, data for students of varying multi-racial heritages are not detailed due to small sample sizes and only the differences between students who identify with one racial group (e.g., White, Asian, or Black/African American) are examined. Future work will seek to add to these smaller sample sizes over time such that statistically significant results can be obtained. In all data presented, sample mean scores and standard deviations (SD) are reported along with mean differences and statistical significance values when comparisons between groups are made.

Initially, STEM (n=647) and non-STEM (n=64) students in the survey population were considered and compared in terms of their mean scores on the AE construct subscales. In each of these subscales, no statistically significant differences were observed between the STEM versus non-STEM student groups using one-way ANOVA: MP $F(1,709) = 0.762, p = 0.383$; META $F(1,709) = 0.415, p = 0.52$; GB $F(1,709) = 0.133, p = 0.715$; EPIST $F(1,709) = 1.397, p = 0.238$. Potential differences between STEM and non-STEM student participants were, therefore, not considered in this work. It is, however, possible that the small sample of non-STEM students impacted these results and future work will revisit and reassess potential differences in AE scores by major as more data has been collected. As this study deals with first-year incoming students and Stevens is a STEM-focused school where even the more liberal arts majors are generally offered with a STEM focus, it is feasible for the AE scores of the incoming class to be similar, independent of major.

Table 2 details the mean AE subscale scores of men and women in the survey population along with the standard deviation (SD) in mean score. Data were analyzed using oneway ANOVA in a sample population that also included non-binary students (n=8). Data for non-binary students is not shown here due to low sample size. When comparing men versus women, there were significant differences in the mean scores in all four dimensions of the AE framework with women scoring higher than men in multiple perspectives (MP), metacognition (META) and epistemology (EPIST), while men outscored women in goals and beliefs (GB). ANOVA indicated that these differences between men and women were were statistically significant: MP $F(1,701) = 8.069, p = 0.005$; META $F(1,701) = 9.153, p = 0.003$; GB $F(1,701) = 3.578, p = 0.049$; EPIST $F(1,701) = 5.648, p = 0.018$. These results suggest that women start their college careers with a greater degree of adaptivity than their male counterparts.

Table 2: AE data comparing men (n=454) to women (n=249) students.

	Men (n=454)		**Women (n=249)**		**Oneway ANOVA (*F=701*)**		
	Mean	**SD**	**Mean**	**SD**	**F-value**	**p-value**	**Mean Diff.**
MP	3.8461	0.52947	3.9671	0.56021	8.069	0.005	-0.12109
META	4.187	0.59312	4.3284	0.59244	9.315	0.003	-0.14144
GB	3.9587	0.57667	3.8768	0.49545	3.578	0.049	-0.08194
EPIST	4.3304	0.57305	4.4403	0.59298	5.648	0.018	-0.10992

When the survey population is broken down by race (Table 3), statistically significant differences (oneway ANOVA, post-hoc Bonferroni) between White, Asian, and Black/African American students were only found between White and Asian students in multiple perspectives (MP) and goals and beliefs (GB): MP $F(2,650) = 5.881, p = 0.003$; META $F(2,650) = 1.656, p = 0.192$; GB $F(2,650) = 3.032, p = 0.049$; EPIST $F(2,650) = 2.553, p = 0.079$ (Table 3 data reports Bonferroni statistics). Multi-racial students identifying as (at least) both White and Asian were also included in the examination of survey data but values are not reported here as no statistically significant differences were observed for this group as compared to White students. In terms of White and Black/African American students, no statistically significant differences were observed in any of the AE survey data when White, Black/African American and multi-racial students were compared: MP $F(2,516) = 0.697, p = 0.498$; META $F(2,516) = 0.390, p = 0.677$; GB $F(2,516) = 0.125, p = 0.883$; EPIST $F(2,516) = 1.525, p = 0.219$.

Table 3: AE data comparing White (n=466), Asian (n=154), and Black/African American (n=22) students.

Race	**White (n=466)**		**Asian (n=154)**		**Post-hoc Bonferroni (White-Asian)**		**Black / African American (n=22)**		**Post-hoc Bonferroni (White-Black/ African American)**	
	Mean	**SD**	**Mean**	**SD**	**p-value**	**Mean Diff.**	**Mean**	**SD**	**p-value**	**Mean Diff.**
MP	3.9436	0.55527	3.7718	0.52636	0.002	0.1718	3.9215	0.42943	1	0.02209
META	4.2778	0.61588	4.1797	0.53116	0.228	0.09812	4.1768	0.53962	1	0.10101
GB	3.9652	0.56119	3.8427	0.50817	0.052	0.12252	3.9615	0.56064	1	0.00368
EPIST	4.4244	0.59648	4.3014	0.54827	0.073	0.12301	4.197	0.58285	0.244	0.22745

White non-Hispanic (n=392) and Hispanic (n=113) students were also compared as shown in Table 4. Significant differences were found only in the category of epistemology, where White, non-Hispanic students outscored Hispanic students by 0.21 survey points: MP $F(2,530) = 0.136$, $p = 0.873$; META $F(2,530) = 0.627, p = 0.535$; GB $F(2,530) = 1.427, p = 0.241;$ EPIST $F(2,530) = 5.423, p = 0.005.$ Data for multi-racial Hispanic students was also included in the oneway ANOVA analysis but is not shown here given the small sample size of this sub-population.

Table 4: AE data comparing White, non-Hispanic (n=392) to Hispanic (n=113) students.

	White,non-Hispanic (n=392)		Hispanic (n=113)		Post-hoc Bonferroni	
	Mean	**SD**	**Mean**	**SD**	**p-value**	**Mean Diff.**
MP	3.9359	0.56442	3.9324	0.52277	1.0	0.00352
META	4.2803	0.62405	4.2085	0.58853	0.809	0.07187
GB	3.9666	0.56693	3.9117	0.55889	1.0	0.05495
EPIST	4.4521	0.58717	4.2448	0.62664	0.004	0.20726

The breakdown of scores along the AE construct subscales for low-income students is provided in Table 5. In this data it can be seen that the AE results for low-income students only differ significantly in a statistical sense (t-test) from non-low-income students in the dimension of epistemology: EPIST $t(707) = -3.295,\ p = 0.001$. This dataset is of particular interest for this study as this research forms part of a larger project assessing the impact of a structured mentoring program in developing aspects of AE within the low-income student population.

Table 5: AE data comparing low-income (n=138) to non-low-income (n-571) students.

	non-Low-income (n=571)		Low-income (n=138)		t-Test Statistics		
	Mean	**SD**	**Mean**	**SD**	**t-value**	**p-value**	**Mean Diff.**
MP	3.39102	0.55851	3.8215	0.42847	-1.718	0.86	-0.08876
META	4.2497	0.60702	4.2053	0.54926	-0.784	0.433	-0.04435
GB	3.9443	0.55912	3.8852	0.51516	-1.131	0.258	-0.0591
EPIST	4.415	0.59344	4.2311	0.56736	-3.295	0.001	-0.18393

The data presented here form a baseline against which future gains made by students in the AE subscales can be measured. It is difficult to provide context or meaning for the values given, however, as so little data currently exists concerning typical scores on the AE subscales for any student population. Additionally, these scores may vary between constructs with a score of 4 in multiple perspectives (MP), for example, being “above average” and a score of 3 in goals and beliefs (GB) being above average. Thus, further discussion of the meaning of these results is difficult. Some context can be given to these results, however, via comparison of the mean AE subscale scores recorded in this study to those recorded in the original study of Fisher & Peterson [5]. This comparison is plotted in Figure 2. As is observed in Figure 2, student data collected in this study is comparable to that collected by Fisher & Peterson (Fisher & Peterson data denoted with an "FP") for their first-year students in general and the first-year biomedical engineering (BME) students they examined. Larger differences only exist in the epistemology (EPIST) subscale. Fisher & Peterson's subscale scores collected for faculty are also shown in this plot to add context to the values plotted and to show the potential for growth in these dimensions.

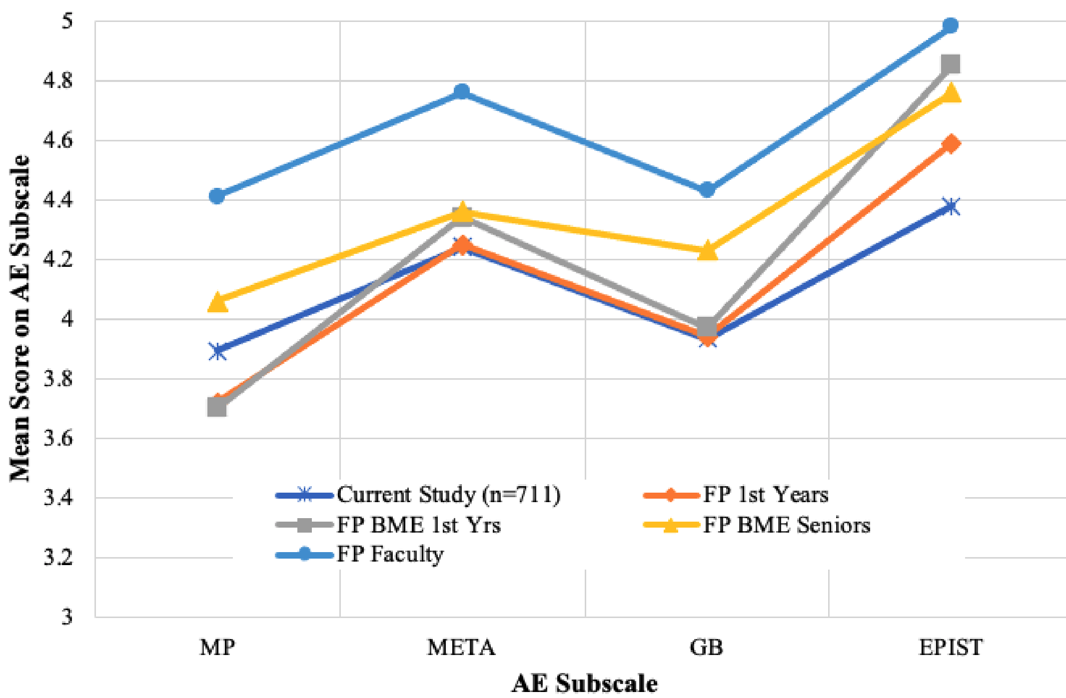

Figure 2: Comparison of AE scores (n=711) from the current study with previous data from Fisher & Peterson [5].

Conclusions and Future Work

The concept of Adaptive Expertise (AE) is used to describe someone with the ability to expand and apply their knowledge to new contexts. Given the increasingly interdisciplinary nature of the workplace and the current needs of the STEM workforce, there is a need for STEM education to foster the traits of AE in the graduates they produce.

An AE survey developed by Fisher & Peterson [5] was used to assess the adaptiveness of incoming students at Stevens Institute of Technology by measuring their predispositions along the four determined constructs of AE: (1) multiple perspectives (MP), (2) metacognition

(META), (3) goals and beliefs (GB), and (4) epistemology (EPIST). A total population of n=711 students completed the survey and data were analyzed to compare mean AE subscales scores between various student groups. Statistically significant differences were found along these scales for men and women, with women outscoring men in three of the four AE subscales (MP, META, EPIST) and men outscoring women in terms of goals and beliefs (GB). Thus it can be said that incoming female students display greater levels of AE than their male counterparts. White students scored statistically higher than Asian students in multiple perspectives (MP) and goals and beliefs (GB), while no statistically significant differences were observed when White and Black/African American students were compared. Epistemology (EPIST) scores for White, non-Hispanic students were statistically higher than Hispanic students, and non-low-income students also scored higher than low-income students on this subscale. To give some context to the reported AE subscale scores, data were compared to that collected by Fisher & Peterson in 2001 [5] and results were observed to be generally consistent with their prior observations.

Future work in this study will involve longitudinal tracking of AE survey data, building on the baseline data reported here, in order to measure adaptiveness as students progress through their program of study. A subgroup of the low-income student population at Stevens will also receive structured mentoring and guidance designed to aid in their development of AE. The adaptiveness of this cohort will then be tracked and compared to various other groups in the survey population in order to test the effectiveness of the AE mentoring and interventions used.

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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.*