

Measuring Skills across the Profile of a Quality Learner and of a Quality Engineer

Tristan T. Utschig¹, Sunni M. Newton¹, and Jeffrey S. Bryan¹

Abstract

We have adapted two previously published profiles to create instruments which measure the attributes represented in the profiles of a quality learner and of a quality engineer on a scale of 1-5. This work is important because it extends the usefulness of the profiles beyond a simple vision or goal state. First, we confirm that the instruments have high face and content validity. Then, we calculate internal reliability coefficients for each of the attributes based on data from approximately 200 students in two different engineering courses. Strong reliability ($\alpha > 0.7$) was found for 12 of the 13 attributes. Next, we compute ranges, averages, and standard deviations among responses for each attribute and find reasonable discrimination among the population tested. We then test the criterion-related reliability of the instrument by correlating ratings for attributes to course and individual assignment grades. Six of the 13 attributes for these two profiles were found to have statistically significant correlations with student grades in the course where the instrument was employed, and numerous significant correlations were found among individual assignments with particular attributes. The attribute of an “achiever” in engineering was most strongly correlated with course and assignment grades. These results imply that quantitative data about student perceptions of skill across the profiles can now be collected and used for program, course, or activity design in order to better achieve learning outcomes and produce high quality graduates. In addition these two instruments can help define for students what critical characteristics they need to develop in order to become excellent learners and engineers. Further, we note that the identified attributes are qualities desirable in many fields. In particular, the instrument for quality engineers, though designed with engineers in mind, is applicable to many fields, needing only minor adjustments to suit the specific needs of the user.

Introduction

We have adapted two previously published profiles—that of a quality learner and that of a quality engineer—to create instruments which measure the degree to which an individual possesses attributes represented in each of those profiles. The instruments ask the user to rate him/herself on a scale of 1-5 for six characteristics (or subscales) of a quality learner and eight characteristics (or subscales) of a quality engineer, where each subscale is measured using several individual items. The instruments are based on the TIDEE profile of a quality engineer (Davis, Beyerlein & Davis, 2005) and on Nancarrow’s (2005) profile of a quality learner. Specifically, in this paper we discuss the process of developing the items for these two instruments and attaching a scale to those items.

We then present efforts to ensure that the instruments are both valid and reliable. First, we explore face and content validity by turning to relevant literature. Then, we explore the results obtained from testing the instruments with approximately 200 engineering students. We calculate the internal reliability coefficients for each subscale of the two instruments. We also analyze reported student self-perceptions of their abilities for each subscale. We quantify the average self-reported ratings of freshman and junior-level students on the six quality learner characteristics and eight quality engineer characteristics, and we compare general trends in these data with similar data from other studies. Finally, as a means to explore criterion-related reliability, we correlate students’ grades to their ratings

of their own abilities. For each subscale we compare the quality learner scale and quality engineer scale results with overall student grades in the courses where the instruments were applied and with grades on selected assignments or parts of assignments in those courses. From these results, we can state that the subscales for these instruments show generally high levels of internal consistency, that student self-perceptions appear to change over time as students move through a program, and that certain subscales of the instruments appear to correlate well with certain types of graded work.

In the last section of the paper, we use our results to discuss specific strategies one might use to help students improve on particular subscales. We also reflect on the overall value of the instruments and how they might be improved through further development and testing. This work greatly extends the usefulness of these two profiles such that quantitative data about student perceptions of skill across the profiles can now be collected and used for program, course, or activity design to supplement other efforts toward better achieving learning outcomes and producing high quality graduates. In addition, these two instruments can help define for students what critical characteristics they need to develop in order to become excellent learners and engineers.

Background

Profiles serve to define the attributes of top performers for specific types of complex tasks. Two profiles, in particular, may be helpful in guiding the development of future

¹Georgia Institute of Technology

engineers as they move through their higher education programs. The profile of a quality learner provides a description of attributes which lead to success in the general academic environment where learning is an explicit requirement supporting nearly all academic activities. The profile of a quality engineer provides a description of attributes that will be required for individuals to become top performers in an engineering work environment. Thus, together, the profiles of quality learners and engineers form a useful set of attributes around which an engineering curriculum can be built.

Nancarrow (2005) has this to say regarding the profile of a quality learner:

Quality learners exhibit definable behaviors that optimize learning and predict successful performance. These behaviors can be classified and assessed. By recognizing these behaviors, learners and instructors can work toward the ideal behaviors, and instructors can design instruction to foster growth in learning behaviors.

The contents of this original profile include six attributes with a total of 34 descriptors comprising these attributes.

Davis, Beyerlein, and Davis (2005) state the following regarding the profile of a quality engineer:

The profile presents technical, interpersonal, and professional skills or behaviors that align with key roles performed by the engineer. The profile is a valuable resource for educators and for students aspiring to become high performing professionals in the field of engineering.

The contents of this original profile include ten attributes with a total of 50 descriptors comprising these attributes.

The content of these profiles is indeed rich. However, the profiles by themselves simply represent a goal state. We identified that, in order to turn these profiles into readily usable measures that might be applied quickly over a broad spectrum of activities, their contents would need to be simplified, and a rating scale would need to be attached to each of the attributes. These modifications would allow both for tracking of changes in the attributes over time, and for the development of targeted activities to build strengths among the various attributes of the profile.

The instruments have been adapted and simplified from their original form in order to:

- produce a more manageable number of skills to be evaluated in an effort to reduce survey fatigue
- isolate skills most relevant to a typical engineering course in order to encourage adoption by faculty and to resonate with the student experience

- produce a consistent grammatical structure for use in a survey format

The result of this activity produced the two instruments shown in Table 1.

Second, a five point Likert scale was used such that students could easily rate themselves on the items related to each attribute. The scale chosen was applied to each item and has the following structure:

5 = very characteristic of me

4 = characteristic of me

3 = moderately characteristic of me

2 = not really characteristic of me

1 = not at all characteristic of me

This scale is used to rate each item for each attribute. From there, scores on individual items comprising an attribute can be averaged to obtain a score for each attribute.

Literature Survey

Next, we explore the face validity and content validity of the instruments by surveying relevant literature. Significant work regarding the face validity of the instruments was conducted during the development of the original version of the instruments as reported by Nancarrow (2005) in her "Profile of a Quality Learner," and in the "Development and Use of an Engineer Profile" (Davis, et al., 2005). These were presented to multiple user groups in a variety of settings and developed with direct input from those groups. Since the only modifications made to the profiles involved simplification and minor grammatical changes, the face validity of the instruments is assumed to remain high. However, in addition to basing our attributes on those identified by Nancarrow and Davis, et al., we surveyed the literature for similar instruments and compared our attributes to theirs, such that we can also establish a reasonable level of content validity.

We found evidence for identification of high level learner characteristics mirroring those outlined by Nancarrow (2005) in several similar research efforts: the recent book *How Learning Works* (Ambrose et al., 2010); a study on self-efficacy and learner competencies for homework practices (Bembenuddy, 2011); and a study on adult learners (Spigner-Littles & Anderson, 1999). Similar studies on growing learner competencies have also been completed, including investigations of undergraduate learning interventions (Norton, Scantlebury, & Dickens, 1999); the learning styles and strategies of language learners (Wong & Nunan, 2011); and learners of English as a foreign language (Jing, 2010). Not only did these studies employ a similar methodology by seeking self-reported data,

Table 1 Adapted profile attributes and individual items for quality learners and engineers***Adapted Profile of a Quality Learner (5 attributes, 20 total items)**

<p>Information Processing</p> <ul style="list-style-type: none"> • Accesses information quickly • Distinguishes relevant from irrelevant information • Learns new tools and technologies to facilitate learning <p>Values</p> <ul style="list-style-type: none"> • Has a vision for life and can articulate goals and objectives with measurable outcomes • Uses learning to clarify personal value system • Respects and values the difficulty and importance of learning • Approaches new tasks with confidence in ability to master new learning <p>Learning Skills</p> <ul style="list-style-type: none"> • Takes responsibility for his or her own learning process • Demonstrates interest, motivation, and desire to seek out new information, concepts, and challenges • Validates own growth and understanding without the need for outside affirmation 	<ul style="list-style-type: none"> • Actively seeks out ways to improve learning skills • Integrates new concepts within a general systems perspective <p>Intrapersonal Skills</p> <ul style="list-style-type: none"> • Focuses energy on the task at hand • Perseveres through difficult tasks, making good decisions about when to seek help • Uses failure as a frequent and productive step on the road to success • Assesses goals and makes appropriate changes to reach them <p>Thinking Skills</p> <ul style="list-style-type: none"> • Clarifies, validates, and assesses his or her understanding of concepts • Applies concepts to new contexts • Transfers and synthesizes concepts to solve problems • Takes appropriate action to get back on track when the planned path is blocked or ineffective
---	---

Adapted Profile of a Quality Engineer (8 attributes, 26 total items)

<p>Analyst</p> <ul style="list-style-type: none"> • Searches strategically to identify all conditions, phenomena, and assumptions influencing the situation • Identifies applicable governing principles of mathematics, natural sciences, and engineering sciences • Extracts desired understanding and conclusions consistent with objectives and limitations of the analysis <p>Problem Solver</p> <ul style="list-style-type: none"> • Examines problem setting to understand critical issues, assumptions, limitations, and solution requirements • Considers all relevant perspectives, solution models, and alternative solution paths • Validates results, interprets and extends the solution for wider application <p>Designer</p> <ul style="list-style-type: none"> • Searches widely to determine stakeholder needs, existing solutions, and constraints on solutions • Thinks independently, cooperatively, and creatively to identify relevant existing ideas and generate original solution ideas • Synthesizes, evaluates, and defends alternatives that efficiently result in products (components, systems, processes, or plans) that satisfy established design criteria and constraints to meet stakeholder needs <p>Researcher</p> <ul style="list-style-type: none"> • Formulates research questions that identify relevant hypotheses or other new knowledge sought • Plans experiments or other data gathering strategies to address questions posed and to control error • Interprets and validates results to offer answers to posed questions and to make useful application 	<p>Communicator</p> <ul style="list-style-type: none"> • Prepares a message with the content, organization, format, and quality fitting the audience and purpose • Delivers a message in a timely, engaged, and credible fashion that efficiently achieves desired outcomes • Assesses the communication process and responds in real time to advance its effectiveness <p>Collaborator</p> <ul style="list-style-type: none"> • Respects individuals with diverse backgrounds, perspectives, and skills important to the effort • Values roles, accepts role assignments, and supports others in their roles • Contributes to development of consensus goals and procedures to promote effective cooperation • Resolves conflicts to promote enhanced buy-in, creativity, trust, and enjoyment by all • Contributes to and accepts feedback and change that support continuous improvement <p>Self-Grower</p> <ul style="list-style-type: none"> • Takes ownership for one's own personal and professional status and growth • Defines personal professional goals that support lifelong productivity and satisfaction • Regularly self-assesses personal growth and challenges to achieving personal goals <p>Achiever</p> <ul style="list-style-type: none"> • Accepts responsibility and takes ownership in assignments • Maintains focus to complete tasks on time amidst multiple demands • Takes appropriate actions and risks to overcome obstacles and achieve objectives
--	--

* All items presented to participants were grouped into the categories as shown in the questionnaire and were not randomized or scattered. Any potential bias introduced to the instrument as a result of this grouping was not investigated.

but they also found high level learner competency traits similar to those identified by Nancarrow (2005).

Likewise, in regards to competencies associated with engineering, we reviewed a study evaluating employer perspectives on desirable engineer skills (Lohmann, Rollins & Hoey, 2006); one that projected characteristics that engineers will need in the future (Robinson, Sparrow, Clegg, & Birdi, 2005); a study of engineering aptitudes (Harrison, Hung, & Jackson, 1955); and one that explored the personality profiles from past engineers (Harrison, Tomblen, & Jackson, 1955). All pointed to general characteristics similar to those identified by TIDEE (Davis, et al., 2005) as well as characteristics we focused on for our research, namely, those having the titles “analyst,” “problem solver,” “designer,” “researcher,” “communicator,” “collaborator,” “self-grower,” and “achiever.” Each study used similar evaluation methods, either seeking self-reported data as we did, or gathering experts to identify common characteristics as TIDEE had done, identifying several universally consistent engineering competencies, or competencies toward which engineers should aspire.

In terms of face validity, then, given the similarities between our two instruments and those of others measuring the same or similar attributes, we feel confident that we have created a process-based tool that appears to measure the attributes of a quality engineer and a quality learner that we believe it to be measuring. Further, our general approach to developing profile attributes by developing engineer and learner characteristics is validated by all of the research we surveyed that used measurement instruments similar to our own and which yielded measurements similar to our own. Robinson, Sparrow, Clegg, and Birdi (2005) put it best: “differences between excellent and adequate performance [among engineers] are more likely to be a result of differences in the level of personal attributes, project management skills, and, to a lesser extent, cognitive strategies and cognitive abilities,” and therefore instruments affecting improvement on those skills may be used in conjunction with targeted activities to help grow competent engineers.

Results

Instrument Analysis

Reliability of Internal Consistency

One major aim of this research effort was to assess the functionality of the learner and engineer profile instruments among several distinct samples of undergraduate engineering students. Reliability of internal consistency is a key criterion for evaluating the instrument, as this metric allows us to assess how

well the items in a given scale “go together,” or tap a single construct rather than multiple, related constructs. Cronbach’s alpha values were calculated for each of the 13 attributes or scales (5 for learners and 8 for engineers) in order to assess the reliability of internal consistency of these two instruments (see Table 2). Given that the alpha values should not be expected to vary by class standing, the four freshman groups and one junior group were combined into a single sample for this analysis, resulting in a sample size varying from 149 to 163 (Ns vary due to missing data from some students on some subscales). In their 1994 book, Nunnally & Bernstein offer a generally acceptable cutoff of $\alpha \geq 0.70$ for analyses completed “in the early stages of predictive or construct validation research.” Using this cutoff, all but one of the 13 profile scales (information processing) exceed this value and as such all but one have acceptable alpha values within this sample.

Table 2 Cronbach’s α values for 13 profile scales, combined (freshmen & juniors) sample

Scale	N	alpha	# items
Information Processing	163	0.559	3
Values	159	0.797	4
Learning Skills	159	0.8	5
Intrapersonal	160	0.74	4
Thinking	161	0.799	4
Analyst	148	0.72	3
Problem Solving	149	0.778	3
Designer	147	0.782	3
Researcher	148	0.906	3
Communicator	148	0.885	3
Collaborator	149	0.818	5
Self-Grower	149	0.773	3
Achiever	149	0.794	3

Basic Results

The next step in assessing the overall functionality of these instruments was to calculate ranges, means, and standard deviations for the freshman and junior samples. These data are presented in the two tables on this page (Table 3 for the four freshman samples combined, and Table 4 for the junior sample). The minimum and maximum values in the tables here represent a single student’s average rating across each descriptor associated with that attribute. Thus, we see decimals for the minimum values. For the maximum values at least one student rated him or herself at the highest level for each descriptor associated with an attribute, and thus each

Table 3 Ranges, means, and standard deviations for the freshman sample (4 semesters combined)

Attribute Name	N	Minimum	Maximum	Mean	Std. Deviation
Information Processing	129	2.33	5.00	4.03	0.56
Values	127	1.50	5.00	4.13	0.69
Learning Skills	125	2.20	5.00	3.95	0.64
Intrapersonal	127	2.00	5.00	3.88	0.71
Thinking	127	2.25	5.00	4.05	0.63
Analyst	118	2.33	5.00	3.95	0.64
Problem Solver	119	1.67	5.00	3.87	0.76
Designer	117	1.67	5.00	3.73	0.75
Researcher	118	1.33	5.00	3.74	0.86
Communicator	118	2.00	5.00	3.92	0.81
Collaborator	119	2.40	5.00	4.33	0.61
Self-Grower	119	2.33	5.00	4.22	0.69
Achiever	119	2.00	5.00	4.25	0.70

Table 4 Ranges, means, and standard deviations for the juniors sample

Full Scale Name	N	Minimum	Maximum	Mean	Std. Deviation
Information Processing	34	3.00	5.00	3.95	0.58
Values	32	2.00	5.00	3.90	0.80
Learning Skills	34	2.00	5.00	3.89	0.73
Intrapersonal	33	2.00	5.00	3.64	0.82
Thinking	34	2.50	5.00	4.05	0.67
Analyst	30	2.67	5.00	3.91	0.67
Problem Solver	30	2.00	5.00	3.70	0.82
Designer	30	2.00	5.00	3.66	0.80
Researcher	30	1.00	5.00	2.96	1.17
Communicator	30	2.00	5.00	3.72	0.83
Collaborator	30	2.80	5.00	4.21	0.62
Self-Grower	30	2.00	5.00	4.06	0.87
Achiever	30	2.00	5.00	4.07	0.83

maximum is listed as 5.00. As shown in the tables, self-reported skills on these scales reflect substantial variation among the student population, though the data tops out at the high end of the scale. Nonetheless, sufficient variation appears to exist such that one can still discriminate among performance levels for different groups.

Student Self-Perceptions

We now look more deeply at how students rate their abilities. We consider the characteristics of each attribute on which freshman and junior-level students tend to rate themselves as particularly high or particularly low, and we

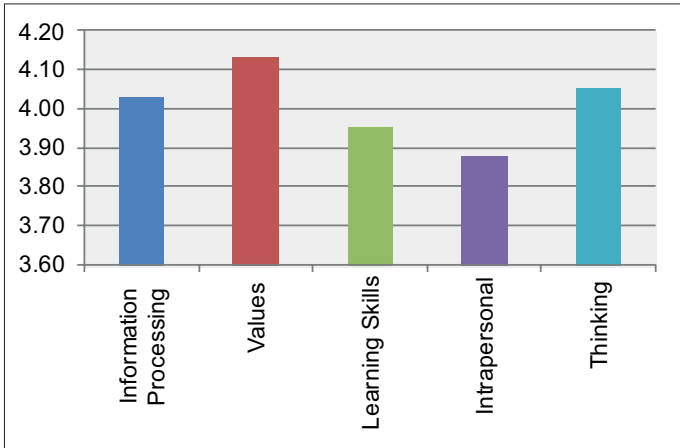
compare general trends in the data with similar data from other studies.

Profile of a Quality Learner

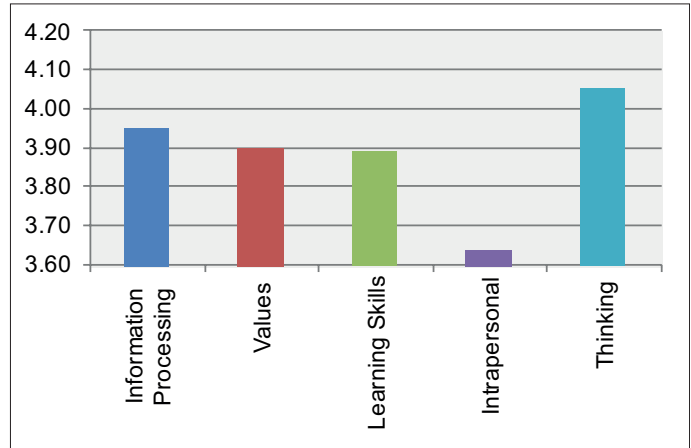
Overall, the students gave themselves very high ratings in all skills. For the learner categories, Figures 1 and 2, freshmen overwhelmingly self-reported score ranges between 3.8 and 4.2, while juniors reported slightly lower scores between 3.6 and 4.1. That said, there were some marked differences in how freshmen scored themselves compared to the juniors. Most distinctly, the freshmen scored themselves noticeably higher in almost all skill

Figures 1 & 2 Average self-reported learner ratings for each attribute by year

Freshmen Learner Values

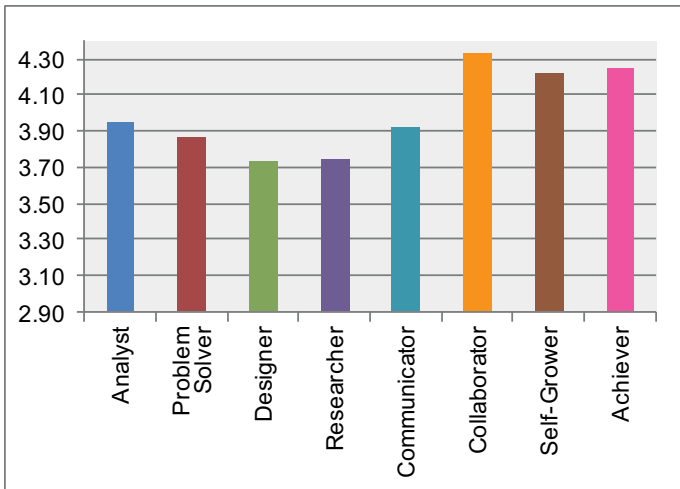


Juniors Learner Values

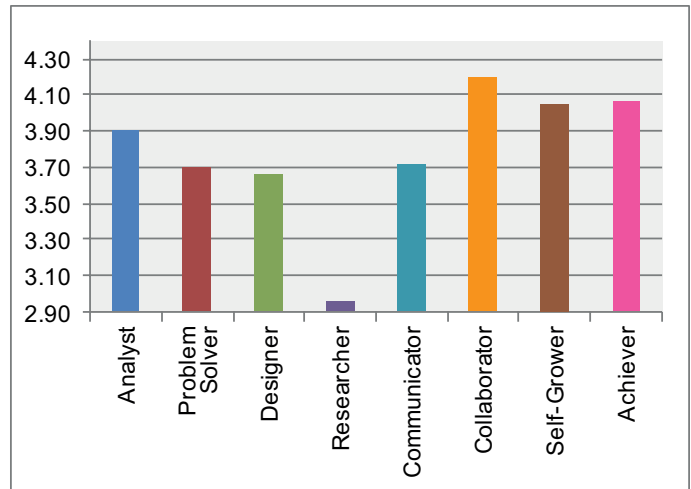


Figures 3 & 4 Average self-reported engineer rating for each attribute by year

Freshmen Engineer Values



Juniors Engineer Values



sets; however both groups scored themselves equally highly as thinkers. Juniors also scored themselves noticeably lower on both the intrapersonal skill set and the values skill set, while they indicated a more marginal difference for information processing and learning skills.

Similarly, for the engineer categories, in Figures 3 and 4, on average students gave themselves high ratings for each attribute. The freshmen overwhelmingly favored score ranges between 3.7 and 4.4, and the juniors favored score ranges between 2.9 and 4.2. In contrast to the scores in the learner categories, between the freshmen and the junior scores, every skill in the engineer category saw a general scoring trend change. The juniors scored themselves marginally lower than the freshmen in all skill sets. And while both groups marked the collaborator skill with their highest scores for any skill set, the juniors marked the researcher skill set with

their lowest scores for any skill set—quite noticeably lower than the freshmen had marked that same skill.

As a general rule, one might expect engineers to rate themselves highly for all of these measures. Based on the psychological study on professional engineers done by Ross Harrison, Winslow Hunt, and Theodore Jackson in 1955, engineers score higher than the general population on the Wonderlic general aptitude test (aptitude for learning and problem solving), and on tests measuring vocabulary, abstract reasoning, arithmetic reasoning, mechanical comprehension, and space relations. On each test, it is rare for the engineering group to fall below 10% of the mean scoring range of the general population. The mechanical comprehension test even measured freshmen engineering students compared with both professional engineers and the general population, finding the freshmen mean score to be higher than that

of the general population (38.5 v. 29.1) but below that of professionals (38.5 v. 46.5).

We take Harrison's evaluation with a grain of salt, since it was done in the 1950s, and the population has since then become generally more literate and with a higher percentage attending college. Nonetheless, their findings still coincide, in a general sense, with GRE data on scoring averages for graduated engineering students from 2008; they find that the engineering mean scores, across multiple engineering fields, in both quantitative and analytic writing are very high, averaging well above average scores for non-engineering students (ETS, 2007). Further, the freshmen we studied are students from a college in which the GPA of newly admitted students trends upward, year to year, with the mean GPA of entering freshmen in 2002 at above 3.7, compared with an average slightly higher than 3.5 in 1993. Not only do engineers, in general, score high in tests that measure the skill sets we evaluated, but the students we measured came into our program with high grades and a certain measure of academic success (Rahnema, 2007).

We can account for the drops in scores for some of the specific skills by citing Harrison, Tomblen, and Jackson (1955), who developed, in conjunction with the engineer aptitude profile, a personality profile of engineers that seems to ring true. They concluded that engineers tend to "avoid introspection and self-examination," which seems to reflect the drop in their evaluations of their intrapersonal skills, and they tend to have "a fundamental aversion to ambiguity" preferring instead to defer to authority, a personal preference that might make such persons less inclined to conduct their own research. Both freshmen and juniors' highest scores are in the collaboration and achievement skill sets, two areas that also correspond well with the general profile of the engineer: for engineers, "[i]nterpersonal relations are harmonious," and "[m]ost of them are goal-oriented" and "[a]dvocates of the direct action approach" (Harrison, et al.). It is possible that through engineering training from freshmen year to junior year, students might simply attenuate within some of these characteristics. That said, one might also expect to see that some of the traits common among engineers would rise while attenuated skills fall, but the previously postulated general drop in self-confidence might explain that discrepancy.

We suggest that the generally high intellectual ability and recent academic success of freshman engineering students, coupled with the relative difficulty of the engineering program at the institution where this study was conducted, as well as the general personality

profile of engineers, may, in part, drive the finding that juniors, on average, might score themselves lower than freshmen on most of the skill sets we studied. High expectations, consistent and persistent academic challenges, and the knowledge that one's peers have the same high-level credentials as oneself would knock anyone's self-confidence down a peg. Further, the student populace from our study is known for its all-work, no-play mentality. It is likely the case that, to an extent, one factor contributing to the drop in self-scoring reported by juniors, compared with freshmen, is simply a more realistic self-perception through a bit of strenuous academic humbling.

Relationships between Student Self-Perceptions and Performance

We have also computed correlations between students' profile ratings with their grades, both for the course as a whole and for specific assignments within the course. In an effort to assess the criterion-related validity of the profiles, scores on each of the 13 attributes were correlated with overall course grades. These analyses were conducted for the freshman samples only, as the sample of juniors was too small for such statistical analyses. It was expected that grades would correlate positively with scores on all profiles, so 1-tailed Pearson correlations were conducted. Results from this analysis for the combined freshman sample are presented in Table 5.

Significant positive correlations with final course grades were found with 6 of the 13 profile scales. These correlations were all fairly small in magnitude, with the strongest correlation being found between the achiever attribute scores and final course grades ($r = .31, p < .01$).

Additional correlations were run with specific assignments or parts of assignments within the freshman course. A large number of significant correlations (48) at the $p = 0.05$ level were revealed from this analysis. To simplify the discussion, only the most prominent results, significant at or below the $p = .005$ level, are displayed in Table 6. Of these, the results most highly correlated with various profile attributes were those from the "Topics Portfolio" assignment, where students choose a topic of interest to themselves within the course context and report on it from a variety of perspectives. This assignment made up between 30 and 40% of the course grade depending on which year the course was offered. Of note, the assignment appeared to correlate most strongly with the "values" and "learning skills" attribute of a quality learner, in addition to the "achiever" attribute of a quality engineer.

If we revert to the less stringent criteria required to make a correlation significant, and we count the number of times

the $p > 0.05$ criterion is achieved as the figure of merit for assignments correlating to profile attributes (there were 48 correlations at this significance level), then the various assignments in the course were correlated most strongly with the attributes of an engineering achiever (12 significant correlations), engineering communicator (7 significant correlations), learner learning skills, learner

values (6 significant correlations) and engineering collaborator and self-grower (5 significant correlations). Of note, the following suite of attributes for engineer (analyst, problem solver, designer, researcher) along with the learner attribute of information processing, had no significant correlation with any aspects of the assignments tested for this paper.

Table 5 Correlations between profile scores and final course grades for the combined freshman sample (4 semesters)

Attribute	Correlation Value (with final course grade)	P-value (1-tailed)
Learner		
Information Processing	0.024	0.393
Values	0.169*	0.029
Learning Skills	0.17*	0.029
Intrapersonal	0.164*	0.033
Thinking	0.021	0.406
Engineer		
Analyst	-0.019	0.42
Problem Solver	0.097	0.148
Designer	-0.009	0.46
Researcher	0.042	0.326
Communicator	0.187*	0.021
Collaborator	0.057	0.268
Self-Grower	0.159*	0.042
Achiever	0.305*	0
Significance		
* = $p < .05$		

Discussion

From the results presented here, it would appear that particular types of assignments might be used to stress the development of particular attributes of quality learners and engineers. For example, to develop learning skills one might assign SIIs or multi-faceted writing assignments such as a topics portfolio. Student choice in what they study, via the topics portfolio, also appears to align well with the values attribute of a quality learner. However, if grades are to correlate to these attributes, one would likely need to align the performance criteria and/or rubric for the assignments with the desired attributes. In the course analyzed for this study, a Process Education™ course design methodology was used to create the course. This course design process inherently included content aligned with a number of the attributes present in these two profiles, and this may be the reason that a number of significant correlations between assignment grades and profile attributes were revealed.

In general, the results here appear to indicate alignment between certain attributes of a quality engineer or learner and student grades on specific coursework. Assignments carefully designed by the course instructor to tap into some of these specific learner and engineer profile behaviors appear to have done exactly that in several cases. Also, correlations of some attributes with overall course grades suggest a possible link between certain learning behaviors and engineering course performance. Given the strong

Table 6 Correlations between profile scores and individual assignment grades for the combined freshman sample (4 semesters)

Graded Assignment	Attribute	Correlation Value (with the graded assignment)	P-value (1-tailed)
Initial Topics Portfolio Overall	Values	0.254	0.003
	Learning Skills	0.244	0.004
	Achiever	0.348	0
Team Presentation	Communicator	0.234	0.005
Final Topics Portfolio Tech Specs	Values	0.266	0.002
	Achiever	0.287	0.001
Final Topics Portfolio Problem Solver	Communicator	0.244	0.005
	Achiever	0.275	0.002
Final Topics Portfolio SII	Learning Skills	0.243	0.004
	Communicator	0.257	0.003

evidence for internal consistency reliability of these scales and the preliminary results that the scales relate in expected ways with various performance measures, these instruments show promise for use in efforts to help students both develop their skills with respect to the various learner and engineer profile attributes, and to increase their awareness that such skills are an important part of their academic and professional development.

Moreover, the two courses where these instruments were employed were designed to foster a metacognitive approach about learning on the part of students. This was achieved in several specific ways:

- Students self-assessed their work in the course on an ongoing basis. Work was reported using a portfolio accumulated during the semester. This was turned in every few weeks and scored via rubric. Students were then allowed to revise their work based on the results from the rubric and from their self-assessments.
- Instructors had the option to assess students' work at any time. This was provided using the SII feedback format (strengths, areas for improvement, insights) that the students were asked to use in self-assessing their work (Wasserman & Beyerlein, 2005).
- Various learning performance tasks were observed in the classroom. On-the-spot feedback was provided by the instructor. Team roles were used from time to time to elevate quality via active reflection. Peer assessment was used on a few occasions before reporting out.

We found that students in this study appeared to be relatively accurate self-assessors, particularly when we correlated self-reported results from our instruments with grades assigned during the course. This is consistent with other studies of student self-assessment, including those mentioned in our literature review. Further, we suggested in previous work related to student aptitude growth and self-assessment that students create significant movement in developing the characteristics of a quality learner when they are exposed to ongoing reflective practice about their learning in the course (Utschig, 2007). Based on that early data, regular self-assessment appears to help develop the skills necessary to improve upon personal learning skills and attributes. Thus, continued self-assessment then reinforces a positive cycle of growth and improvement that may help to explain why the students in this study were such accurate self-assessors. However, further research is needed before this claim can be firmly supported. A beginning point for that work is outlined in the conclusions which follow.

Conclusion

Finally, we reflect on the overall value of the instruments and how they might be improved through further development and testing. First, the information processing attribute showed a relatively low internal consistency. This attribute may need to be revised. Only three of the original six items describing this attribute were used in the measurement instrument. Different items might be selected, or more items might be used to measure this attribute. Second, the instrument needs to be tested with larger numbers of students in different courses which more directly address the development of certain attributes such as the engineering "designer." No correlations with any grades in the course were found for this and several other attributes, but this makes sense for a number of these attributes, as they were not emphasized in the course. Third, the instrument might benefit from a modified scale. Another and perhaps more common formulation of the particular Likert scale used for the instrument would use "not at all," "slightly," "moderately," "very," or "extremely" characteristic of me. This scale modification would essentially remove one of the lower options ("not really") and another add a higher option ("extremely") to the current scale, thus possibly reducing positive bias and increasing the discriminatory capability of the instrument.

Future work with these instruments will focus on two areas. First, in conjunction with establishing a baseline, we also asked students to rate themselves on perceived change over the course of the semester, on a scale from -3 to +3, for each item. Analysis of this change data for profile characteristics may provide further evidence for the potential effectiveness of the instrument when used in conjunction with a course or program to promote student growth. In particular, it may also highlight the value of student self-assessment toward learning and aptitude development (as measured by these instruments) indicated in our literature survey.

These two instruments can help educators develop targeted activities and assignments that build key personal and professional skills for students. They can also assist schools in measuring student abilities relevant to learning outcomes that are difficult to assess. Finally, they can help define for students what critical characteristics they need to develop in order to become excellent learners and engineers.

References

- Ambrose, Susan A., Bridges, M., DiPietro, Lovett, M. C., Norman, M. K., & Mayer, R. E. (2010). *How learning works: 7 research-based principles for smart teaching*. San Francisco: Jossey-Bass.
- Bembenuddy, H. (2011). Meaningful and maladaptive homework practices: The role of self-efficacy and self-regulation. *Journal of Advanced Academics*, 22(3), 448-473.
- Davis, D.C., Beyerlein, S.W. , & Davis, I. T. (2005). Development and use of an engineer profile. *Proceedings of the Annual Conference of the American Society for Engineering Education*, Portland.
- ETS. (2007). *Guide to use of scores*. Retrieved December, 2011, from ets.org: <http://www.ets.org/Media/Tests/GRE/pdf/994994.pdf>
- Harrison, R., Hunt, W. & Jackson, T. A. (1955). Profile of the mechanical engineer. I. Ability. *Personnel Psychology*, 8(4), 219-234.
- Harrison, R., Tomblen, D. T., & Jackson, T. A. (1955). Profile of the mechanical engineer. III. Personality. *Personnel Psychology*, 8, 469-490.
- Liu, J. (2010). A study on language learning strategies among the instructed EFL learners. *US-China Foreign Language*, 8(3), 36-39.
- Lohmann, J. R., Rollins, H. A., & Hoey, J. J. (2006). Defining, developing and assessing global competence in engineers. *European Journal of Engineering Education*, 31(1), 119-131.
- Nancarrow, C. (2005). Profile of a quality learner. In D.K. Apple, S.W. Beyerlein, & C. Holmes (Eds.) *Faculty guidebook: A comprehensive tool for improving faculty performance* (pp. 41-44). Lisle, IL: Pacific Crest.
- Norton, L. S., Scantlebury, E., & Dickens, T. E. (1999). Helping undergraduates to become more effective learners: An evaluation of two learning interventions. *Innovations in Education and Training International*, 36(4), 273-284.
- Nunnally, J.C., & Berstein, I.H. (1994). *Psychometric Theory*. McGraw-Hill.
- Rahnema, F. (personal communication, 2007)
- Robinson, M. A., Sparrow, P. R., Clegg, C. , & Birdi, K. (2005). Design engineering competencies: Future requirement and predicted changes in the forthcoming decade. *Design Studies*, 26(2), 123-153.
- Spigner-Littles, D., & Anderson, C. E. (1999). Constructivism: A paradigm for older learners. *Educational Gerontology*, 25(3), 203-209.
- Utschig, T. U. (2007). Work in Progress: The Impact of Assessment in a Freshman Course on Growing the Characteristics of a Quality Learner. *Proceedings of Frontiers in Education Conference*, Milwaukee.
- Wasserman, J. & Beyerlein, S.W. (2005). SII method for assessment reporting. In D.K. Apple, S.W. Beyerlein, & C. Holmes (Eds.). *Faculty guidebook: A comprehensive tool for improving faculty performance*. Lisle, IL: Pacific Crest.
- Wong, L. L. & Nunan, D. (2011). The learning styles and strategies of effective language learners. *System*, 39(2), 144-163.