AC 2009-550: EXPLORING COGNITIVE DIVERSITY AND THE LEVEL-STYLE DISTINCTION FROM A PROBLEM SOLVING PERSPECTIVE

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Exploring Cognitive Diversity and the Level-Style Distinction from a Problem Solving Perspective

Key Words: Adaption-Innovation theory, cognitive style, diversity, problem solving

Introduction

The importance of understanding the cognitive diversity of our students (and ourselves, as their instructors) is clear: the more we know about the way they (and we) think, the better we can develop our courses and tailor our teaching to ensure the best and most effective learning experiences possible for the largest number of students. As Felder and Brent[9] note: "Students have different levels of motivation, different attitudes about teaching and learning, and different responses to classroom environments and instructional practices. The more thoroughly instructors understand the differences, the better chance they have of meeting the diverse learning needs of all of their students." Among the models of cognitive diversity available to us, Kirton's Adaption-Innovation (A-I) theory[19] provides special insight with respect to our students' efforts in solving problems. In particular, A-I theory identifies four principal variables that can be used to explain many of the variations we see among our students as they solve problems, namely: *cognitive level* (capacity/resource), *cognitive style* (preferred approach), *motive* (driving force), and *opportunity* (including one's perception of it). In this paper, we will focus on cognitive style, its diversity among our students, and the importance of distinguishing between style and level in engineering education.

In general, *cognitive level* is a unipolar construct that relates to one's mental capacity, both *potential* (e.g., intelligence, aptitude, talent) and *manifest* (e.g., extant knowledge, skill, experience); the latter can be measured in terms of both *type* (i.e., domain – discipline, area of study) and *degree* (i.e., amount – novice, expert) [19,23]. *Cognitive style* is defined as a "strategic, stable characteristic – the preferred way in which people respond to and seek to bring about change" (including the solution of problems) [19]. As such, cognitive style is a bipolar construct that is independent from level; it also has multiple dimensions, including Adaption-Innovation (A-I) and Introversion-Extraversion, among others. Here, we will focus on A-I cognitive style and its assessment using KAI® (the Kirton Adaption-Innovation inventory)[18], which has been rigorously validated and used in a wide variety of contexts, including engineering, business, education, medicine, and the military.

As measured by KAI, an individual's cognitive style is related to the amount of structure he or she prefers when solving problems, with the more Adaptive preferring more structure (with more of it consensually agreed), and the more Innovative preferring less structure (with less concern about consensus). These individual differences are immediately relevant for individual students as they strive to solve problems with varying degrees of structure (e.g., open-ended vs. closed-ended, tightly constrained vs. loosely constrained, etc.) and to meet the expectations of their instructors, whose own styles will influence the solutions they value most. For example, a more Adaptive instructor is likely to expect more careful attention to detail in a completed assignment, while a more Innovative instructor will tend to place higher value on "out-of-the-box" ideas.

The individual differences associated with cognitive style can also have a significant impact on the performance of student teams engaged in collaborative problem solving, particularly when the problems are complex and require diverse views and approaches for their resolution[3,15]. Unfortunately, differences in style are often misinterpreted as differences in level (and the owners of those differences as "inferior"), leading to the undervaluation and poor utilization of potentially critical contributions to the team. In general, when any team comes together to solve a problem, they automatically inherit another problem: the management of cognitive diversity within that team. Kirton refers to these two problems as "Problem A" (the original problem that brought the team together) and "Problem B" (managing their individual differences), respectively[19]; successful teams spend more time on Problem A than Problem B, but this may be no easy feat!

It is also important to note that some scholars (and many practitioners) have become particularly enthralled with Innovation ("radical, breakthrough change") in recent years, which – when framed in problem solving terms – amounts to a bias toward solving problems by changing the current, consensually agreed, cognitive structure (e.g., framework, model, paradigm, standard) *in order* to solve the problem. Others recognize the value of solving problems by *making use of* the current structure – that is, by altering cognitive structure *as an outcome* of solving the problem. Drucker[6] described these contrasting approaches as "doing things differently" or "doing things better", respectively. Adaption-Innovation theory argues that either option (more accurately, any position along the bipolar continuum of which they are a part) may be the right way, depending on the nature of the problem itself – <u>not</u> on a past or present trend, or on the preference of any particular person.

Thus, there is no best style *in general*; every style (level, motive, perception of opportunity) will have advantages and disadvantages *relative to the problem at hand*. This more balanced perspective certainly has implications in engineering, both in terms of educating future engineers and within engineering practice, as other researchers have discussed[3,4,5,14,17,20]. As Lopez-Mesa and Thompson note, for example[20]: "The problem-solving approach taken by a strong Innovator is quite different to that taken by a strong Adaptor. It is not that one is better than another, but rather that the appropriate style be used to obtain the appropriate solution." Once we understand that style is independent from level and that all styles have equal value *overall*, we realize that a diversity of styles within an engineering team is desirable – but this diversity must be understood and managed well, or it may create conflicts (Problem Bs) that distract the team from its main, original aim (Problem A).

With all of these factors and issues in mind, we have begun to explore the cognitive diversity of our students from a problem solving perspective. For example: there is a common misperception (found most often in the creativity literature) that portrays engineers as "highly structured, Adaptor-inclined". Based on personal experience (both in and out of the classroom), we believe this to be a false image of engineers and decided to test its accuracy. In addition, we wanted to explore the cognitive style profiles of students in different degree programs, to see how style and level (in this case, domain of study) were related in that context. Finally, through this preliminary investigation, we hoped to learn more about how the diverse problem solving styles of our students impact their performance and learning experiences – or, at the very least, to uncover directions for future research in this area.

To these ends, we analyzed A-I cognitive style data (collected using KAI over a 6-year period) for 363 students enrolled in a required core course within our Systems Engineering curriculum. This course is also an elective for students in other engineering majors and in other disciplines (e.g., Management, Education). Of the total sample, 327 students were registered in an engineering degree program (Systems Engineering, Software Engineering, or Information Science); additional details about these samples will be provided in a later section. This paper will report on the findings of our analysis, including the range of cognitive styles present among our students, differences in style distributions between genders and among students enrolled in different disciplines and sub-disciplines, and the relationship between cognitive style and GPA (as a measure of performance). We will close with a discussion on some of the practical implications of our findings and the value of distinguishing between level and style, both in the classroom and in engineering practice.

Problem Solving Diversity and the Level-Style Distinction

To describe *problem solving diversity* at its most fundamental, we begin with the process of problem solving itself[17,19]. The first step in this process is to perceive an *opportunity* (assuming it is available and however it may come to one's attention). Next, we must have *motive*, i.e., the allocation of energy (in sufficient amount, over sufficient time) to resolve the question of how to exploit the opportunity. With the problem and the will to solve it in hand, the means to do so are now required: both the right *levels* (inherent potential capacities, as well as manifest abilities, types of knowledge, and skill – which ones and to what degrees) and the appropriate *styles* (preferred characteristic approaches). Both of these general selected means are best determined by the nature of the problem – i.e., what is required for its resolution – not by the current mode of trendy thinking (e.g., "Innovate or die!"), the educational climate, or some dominating peer[14].

In accord with Guilford[12] and Popper[27], Kirton's Adaption-Innovation theory rests on the basic assumption that <u>all</u> human beings are creative and solve problems (indeed, the brain cannot distinguish between the two). As described above, we do so with different capacities (levels) and in different characteristic ways (styles). Messick contrasted the properties of cognitive styles and intellectual abilities (i.e., cognitive level), noting that "abilities are seen as unipolar, whereas cognitive styles are typically conceived to be bipolar"[23]. That is, abilities range from none to a large amount with a socially preferred end, while cognitive styles range from one extreme to a contrasting extreme, with no socially preferred end (see Figure 1).

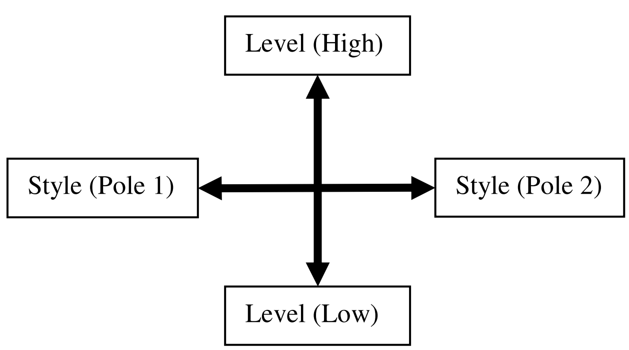

Figure 1: Independence of cognitive level and cognitive style[16]

Both cognitive level and cognitive style have multiple dimensions, each of which may be measured using an appropriate psychometric instrument. *Potential capacity (level)* can be assessed through intelligence tests, aptitude tests, and/or talent evaluations, while *manifest capacity (level)* may be assessed in terms of learned skills, knowledge, and/or expertise. We are familiar with these various forms of level and their assessments in the educational domain, where a student's potential level is often used to determine whether or not they should participate in "advanced placement" programs, and both potential and manifest level (e.g., Scholastic Aptitude Tests and grade point averages, respectively) may be used to determine whether a student is prepared to enter a particular college degree program.

One of the most familiar dimensions of *cognitive style* may be Introversion-Extraversion, which is often (although not the most accurately) measured using the Myers-Briggs Type Indicator (MBTI®)[24]. Torrance's Left/Right Hemisphere Style of Thinking (measured via an instrument of the same name[33]) and Adaption-Innovation (measured via KAI[18]) are more examples. Kirton and others have demonstrated the independence of cognitive style and cognitive level through numerous studies[19]; thus, information about an individual's cognitive level (capacity) provides no information about that person's cognitive style (preferred approach), and vice versa. Kirton is not the only scholar to support a sharp distinction between level and style. In their review and synthesis of cognitive style theory over several decades, Sternberg and Grigorenko[31] define styles (in general) as a set of preferences, explicitly distinct from abilities (i.e., level); this view is reflected by Zhang and Sternberg[35,36] as well.

Yet, there are others who confound the two – as Sternberg and Grigorenko also note[31]: "both successes and failures that have been attributed to abilities are often due to styles". In addition, some creativity scholars[1,28,29] put style in direct relation to a process (e.g., the Creative Problem Solving process), where they associate "preferences" with the stages of that process (e.g., problem clarification, idea generation, solution development, etc.) and refer to them as "creativity styles". In this view, every individual has a preference for a particular stage within the creative process, and so, spends more time there, increasing their "natural ability" for it, as well as developing the thinking skills that are needed in that stage. Clearly, there is confusion here between preference (style), learning (level), and their combined progress toward a solution that is separate from both.

Adaption-Innovation theory also helps sort out this confusion by distinguishing between process (a general, idealized template for problem solving) and technique (a specific learned method for making best use of our problem solving faculties) – with both of these being separate (also) from level and style. Within a process (which is defined by its stages and the ideal order in which they are to be carried out), any style and any level can be applied independently in any stage, and any technique can be used as well. This is not to say that all styles, levels, and techniques are equally appropriate in every stage of a *particular* process, but the stage itself does not define any of the three. So, for example, within Guilford's model of the thinking process (i.e., cognition → memory → divergent operation → convergent operation → evaluation)[12,18], the divergent operation can be carried out at high to low level and more Adaptively to more Innovatively – and using any relevant technique. Likewise, Guilford's convergent operation can also be implemented using any combination of level, style, and technique. From this we see that there are no mutually exclusive groups of "divergent thinkers" and "convergent thinkers" – despite what many popular business and self-help books seem to suggest. All humans (all brains) both diverge and converge, with different degrees of aptitude and skill, and in a variety of characteristic ways.

Digging even deeper into style, Kirton[19] notes that one's preference appears to be well set, with research showing that (at least) it is set early[30,32] and with hints that there is a genetic link[34], as is supposed with all dimensions of personality[7]. *Behavior*, on the other hand, must be assumed to be more flexible – enabling an individual temporarily to depart (in action) from his or her fixed preference when the need for such a change is perceived. However, operating outside one's preference is harder (more costly) to undertake and is likely only for as long as it is needed (i.e., preference reasserts itself when we perceive that the need to act differently is no longer present).

Describing and Measuring Adaption-Innovation Cognitive Style

As measured by KAI (the Kirton Adaption-Innovation inventory[18]), cognitive style differences lie on a bipolar continuum that ranges from strong Adaption on one end to strong Innovation on the other (see Figure 2). The main pattern that differentiates among these preferences (remembering that it is a continuum of style, not a dichotomy) is the characteristic way in which an individual manages structure. Individuals who are more Adaptive prefer to solve problems using more structure, and with more of this (cognitive) structure consensually agreed. In contrast, more Innovative individuals prefer to solve problems using less structure and are less concerned with gaining consensus around the (cognitive) structure they use (although even the most Innovative do want their solutions accepted!).

To go a bit further: those who prefer the Adaptive strategy (strictly: those who are more Adaptive) tend to approach problems from within the given, accepted, frame of reference (i.e., model, standard, paradigm – all cognitive structures), looking for solutions that are more immediately effective, sound, and reliable. These individuals bring value through consistency, stability, and efficiency, all of which keep "the system" running smoothly in both the short and the long term. Their advantage lies in their preference for finding ways to enable and create change *within* a structure, making best use of its defining properties and resources, changing the structure *as an outcome* of solving a problem. Their disadvantage is their tendency to hold on to a structure "too long" – i.e., even when its usefulness is being overshadowed by its faults[14,17].

On the other hand, those who prefer (cognitively) the Innovative strategy (strictly: those who are more Innovative), often work more at the edges of a structure, or they may even detach a problem from its customary frame of reference, searching for unorthodox solutions in unexpected places. The value of this approach is also clear: it can provide a more dramatic shift in structure when such a shift is required. It is also riskier – altering, from time to time, even the most fundamental elements of the structure *in order* to solve the problem. The advantage of the more Innovative lies in their preference for manipulating boundaries and combining information in ways that their more Adaptive peers may miss; their disadvantage is their tendency to cast off a structure "too soon" – i.e., when it is still useful, despite its faults[14,17].

The Kirton Adaption-Innovation Inventory (KAI) was introduced in 1976 and measures preferred problem solving (cognitive) style only[18]. Respondents answer a list of 33 questions that focus on how easy or difficult it is for a person to behave consistently, over a long period of time, in particular ways; each answer is assigned a value using a 5-point scale. The inventory is designed for adults with work experience, but it has been used with bright children as young as 13 with good results. KAI is easy to understand and can typically be completed in less than 15 minutes. KAI must be administered, scored, and interpreted by a certificated practitioner, each of whom must attend a rigorous training course and maintain their certification through regular continuing education programs.

Felder and Brent[9] note that any psychometric instrument used in the classroom (whether for research or personal development) should be reliable and well-validated; KAI meets these criteria. Initial validation of KAI was based on six general population samples across 10 countries (including the U.S.) with a total of approximately 3000 subjects; the internal reliabilities range between .84 and .89, with a mode of .87[19]. Additional supporting data (derived from the KAI Manual) relating to the instrument's development, validation, and testing may also be found in Kirton's work[19]; in addition, over 300 archival papers and more than 90 graduate theses have been published in support of the underlying theory and the inventory.

As shown in Figure 2, a person's KAI score will fall within a range of 32 to 160 (theoretical mean: 96), with a score of 32 representing the theoretical limit of highest Adaption, and a score of 160 representing the theoretical limit of highest Innovation. In practice, scores typically fall between 45 and 145. For large general populations, the distribution of KAI scores forms a normal curve with an observed mean close to 95 (± 0.5) and a standard deviation of (circa) 17 for all samples[19]. In terms of gender differences, women are (on average) about one third of a standard deviation (i.e., 6 to 7 points) more Adaptive than men, with females' KAI scores normally distributed around a mean of 91, and males' KAI scores normally distributed around a mean of 98. To date, no culture differences have been found in the large sample studies[19]. Smaller, stable groups can be predictably different from general populations, depending on their problem solving orientation, and may exhibit skewed distributions about different means; for example, the observed mean for engineers (in general, across genders) is 96.8[19].

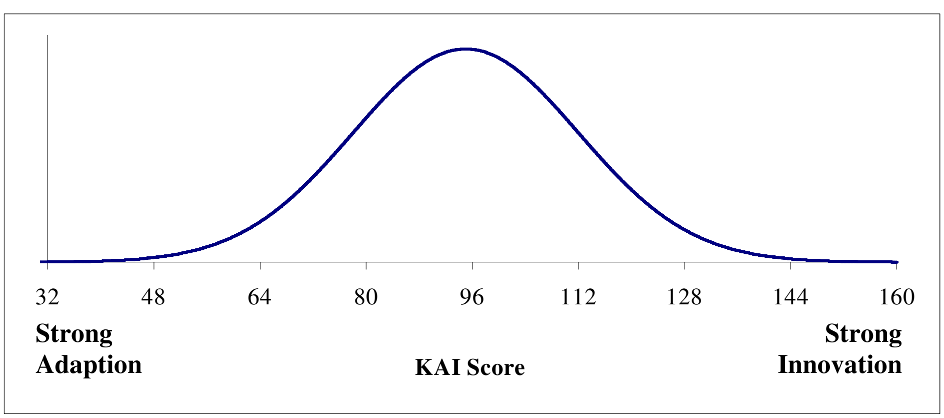

Figure 2: The A-I style continuum with typical KAI distribution for a large, general population

Cognitive Style Diversity Among Our Students

Throughout the years 2002 – 2008, we collected KAI scores for a total of 363 students enrolled in a core course within our Systems Engineering curriculum*. As mentioned earlier, this course is also an elective for students in other engineering degree programs, as well as students enrolled in non-engineering degree programs, such as Management, Leadership Development, and Education (e.g., Instructional Design). Of the total sample we analyzed, 327 students were registered in one of three engineering degree programs (Systems Engineering, Software Engineering, or Information Science), 12 were registered in a Leadership Development degree program (offered by the Management Division), and 24 had undeclared majors at the time of the KAI administration. While these last two sub-groups were too small to yield statistically significant results, we have retained them in our analysis because they suggest some potentially interesting trends when compared with the engineering student sample.

Cognitive Style Diversity within the Total Sample

Figure 3 shows the KAI score distribution for the total sample of students (N=363), along with the range, median, mean, and standard deviation for this sample. A few simple observations can be made here, based on these results. First, overall, the range of scores within the total sample was large (90 points), indicating a wealth of cognitive style diversity within our student population (and disproving the notion of engineers as all "highly structured, Adaptor-inclined"). In addition, the average range of KAI scores *per class section* (generally 25-30 students) was 66.5, which is also wide. As a benchmark for this part of the analysis, the *just-noticeable-difference* (JND) between the problem solving styles of two individuals (or between an individual's style and the mode of a group) is 10 points for KAI, with greater differences (particularly those of 20 points or more) requiring increasing amounts of attention and care[19].

The implications of these results are intriguing: within large samples (e.g., a department or division, multiple sections of a required course, etc.) and even within class sections of moderate size (25 students or more), the data indicate that we can reasonably expect a wide range of preferences among our students for different amounts of structure in the learning environment. In addition to the impact on students' perceptions of assignments, course organization, lecture style, and instructor responsiveness, these differences in style will also impact students' perceptions *of each other* – in class, in teamwork, and in their other working and personal relationships. Further implications of these differences will be discussed in more detail later in this paper.

In addition, we can see from the data that the total sample was skewed slightly towards a more Innovative preference (mean of 97.38) as compared to both the general U.S. population sample (mean of 94.98) and the general engineering sample mentioned previously[19] (mean of 96.8)†. These differences are small, however (in the context of A-I style), and unlikely to be noticed; research suggests that the just-noticeable-difference (JND) between the KAI means of *two groups* is 5 points.[19] With such similar means and distributions, the cognitive climates of these groups are likely to be very similar.

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* We are fortunate to have eight KAI certificated practitioners among our staff at this time.
† The standard deviations were very similar across all three of these samples as well (circa 17).

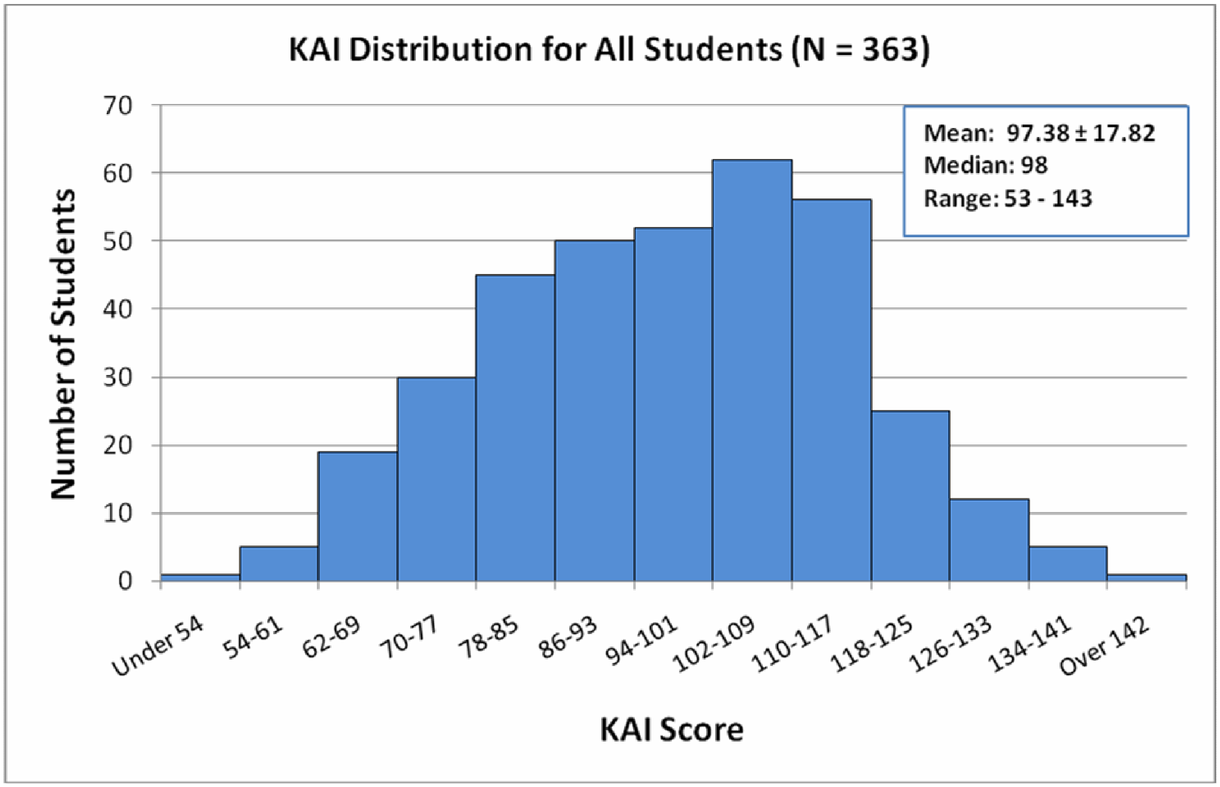

Figure 3: KAI score distribution for total sample

Cognitive Style Diversity Based on Gender

Table 1 summarizes key statistics of the total sample of KAI scores (N=363) and for sub-groups sorted by gender. Figures 4 and 5 present the corresponding distributions of KAI scores for the male and female samples, respectively. (Comments on these data follow the figures.)

STUDENT SAMPLE	SIZE (N)	RANGE	MEDIAN	MEAN	STD. DEV.
All students	363	53 - 143	98	97.38	17.82
Male students only	258	53 - 143	99	97.95	16.82
Female students only	105	57 - 136	95	95.97	20.07

Table 1: Key statistics for KAI scores of total sample (N=363) sorted by gender

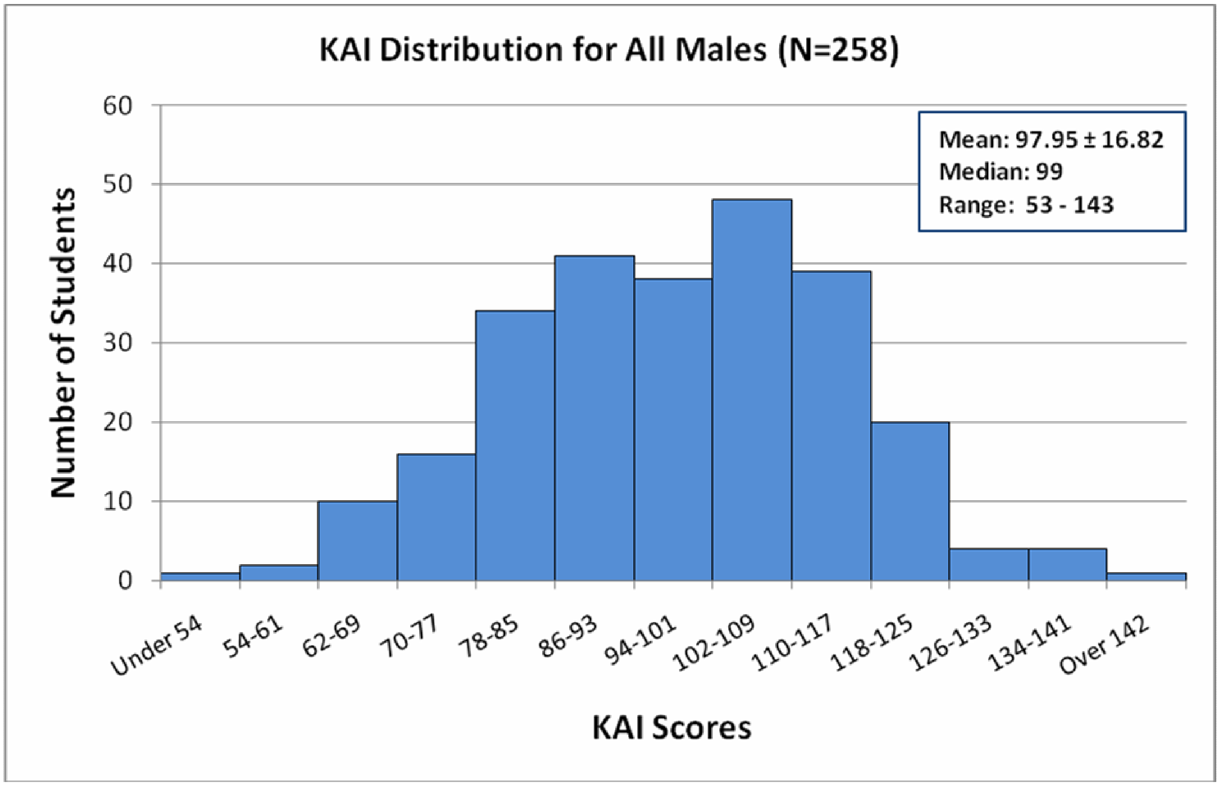

Figure 4: KAI score distribution for male students only

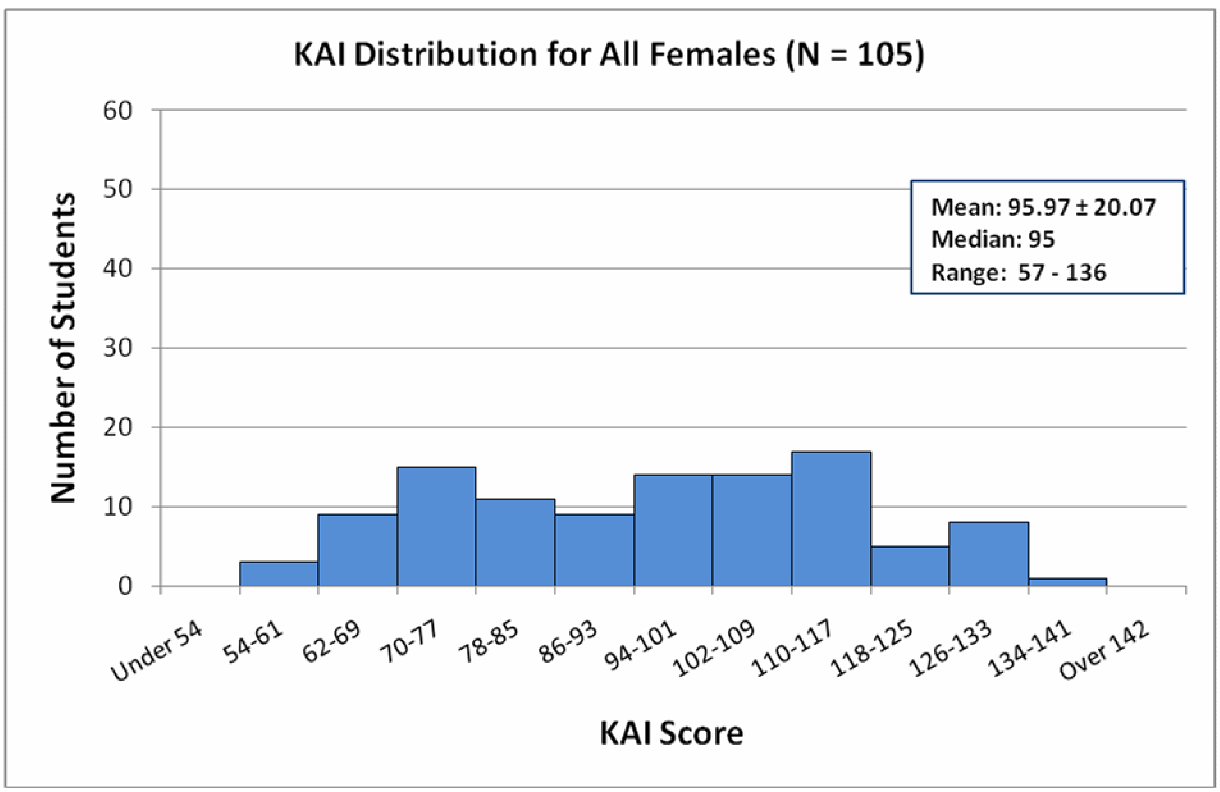

Figure 5: KAI score distribution for female students only

In considering the sub-groups sorted by gender, the male students contained both the most Adaptive and the most Innovative students in the total sample (as expected from general population studies[19]), but the female student group also contained individuals with highly Adaptive and highly Innovative cognitive styles (within a total range of 79 points). While the male students reflected a distribution similar to that of the general male population (mean of 98), the female students (on average) showed a slight skew towards Innovation when compared to the general female population (i.e., mean of 95.97 here, compared to 91 – a difference that is very close to the group mean just-noticeable-difference of 5 points). This result is similar to that obtained by McCarthy[22] for a group of 46 female engineers (mean of 102.5), although in our case, the extent of the skew is not as great.

Such skews may be considered predictable (or, at least, expected) if one considers the late appearance of women in the traditionally male-dominated field of engineering[17]. Returning to our understanding of style as an indicator of preference for structure, previous research shows that those who "break boundaries" (of any kind – conceptual, cultural, gender, etc.) are more likely to be more Innovative[19,22]; this is confirmed here to some degree. These results lead us to ask a number of questions: For example, can we use this information to assist in the recruitment of women in engineering? In looking at the retention of female students, is there any correlation between style and the women who complete engineering programs as opposed to those who leave them? This line of questioning opens up a number of potential areas for future inquiry that may further inform the work of previous researchers[8].

Cognitive Style Diversity Based on Ethnicity

Ethnicity data were available for 273 students within the total sample; we chose to explore cognitive style data for the three largest ethnic groups within that subset (White, Asian, and African Americans, respectively, for a total of 256 students), with the resulting key statistics shown in Table 2. Once again, we note that a wide range of cognitive (problem solving) styles exists within each subset. Although differences between the group means and medians sparked our interest, no statistically significant differences were found among them.

STUDENT SAMPLE	SIZE, N (%)	RANGE	MEDIAN	MEAN	STD. DEV.
White	209 (76.6%)	53 - 141	100	97.95	18.14
Asian	34 (12.8%)	54 - 135	93	93.59	16.70
African American	13 (5.1%)	69 - 129	102	99.92	17.92

Table 2: KAI statistics for the three largest ethnic sub-groups (N_{total}=256)

Cognitive Style Diversity Relative to Academic Major

When considering the level-style distinction, recall that level can be described in terms of both *type* (*domain* of knowledge, skill, etc.) and *degree* (*amount* of knowledge, skill, etc.). Thus, one of the ways we can explore the level-style distinction is to study the cognitive style distributions for students enrolled in different academic majors (domains of study). When grouped by academic major, the KAI data revealed some interesting features and trends. Table 3 summarizes the key statistics for the four academic majors represented in our sample (in order of increasing style means), while Figures 6-9 show their respective KAI score distributions.

ACADEMIC MAJOR	SIZE (N)	RANGE	MEDIAN	MEAN	STD. DEV.
Systems Engineering	147	53 - 138	94	95.19	18.56
Software Engineering	63	54 - 143	98	97.33	16.05
Information Science	117	64 - 136	102	100.03	17.09
Leadership Development	12	69 - 141	110	105.33	23.6

Table 3: Key statistics for KAI scores of total sample, sorted by academic major

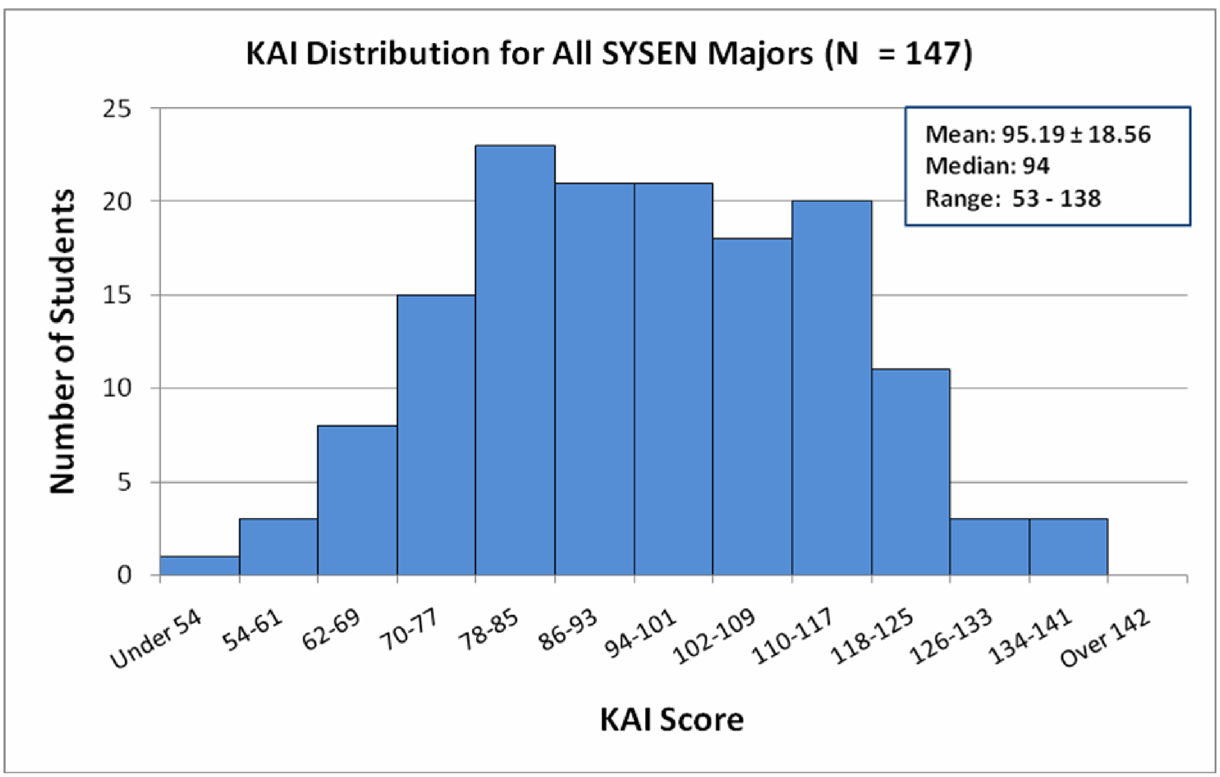

Figure 6: KAI score distribution for Systems Engineering students

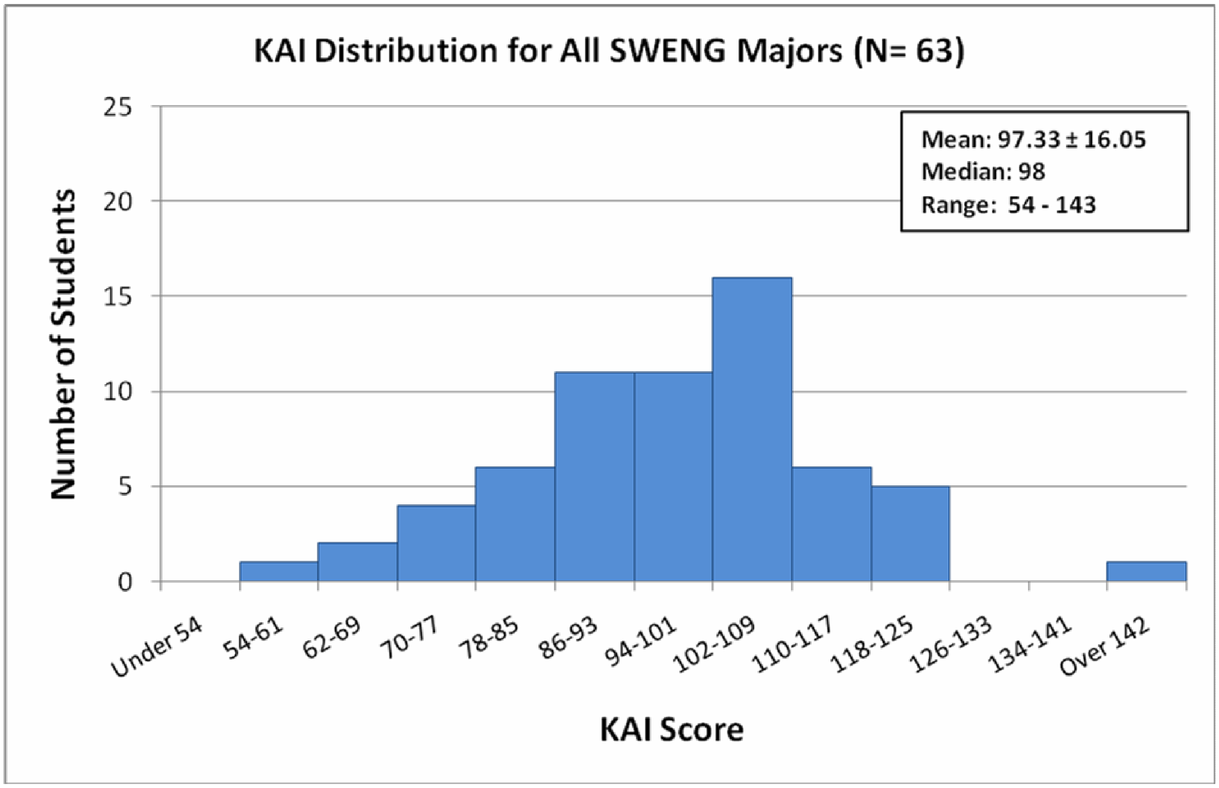

Figure 7: KAI score distribution for Software Engineering students

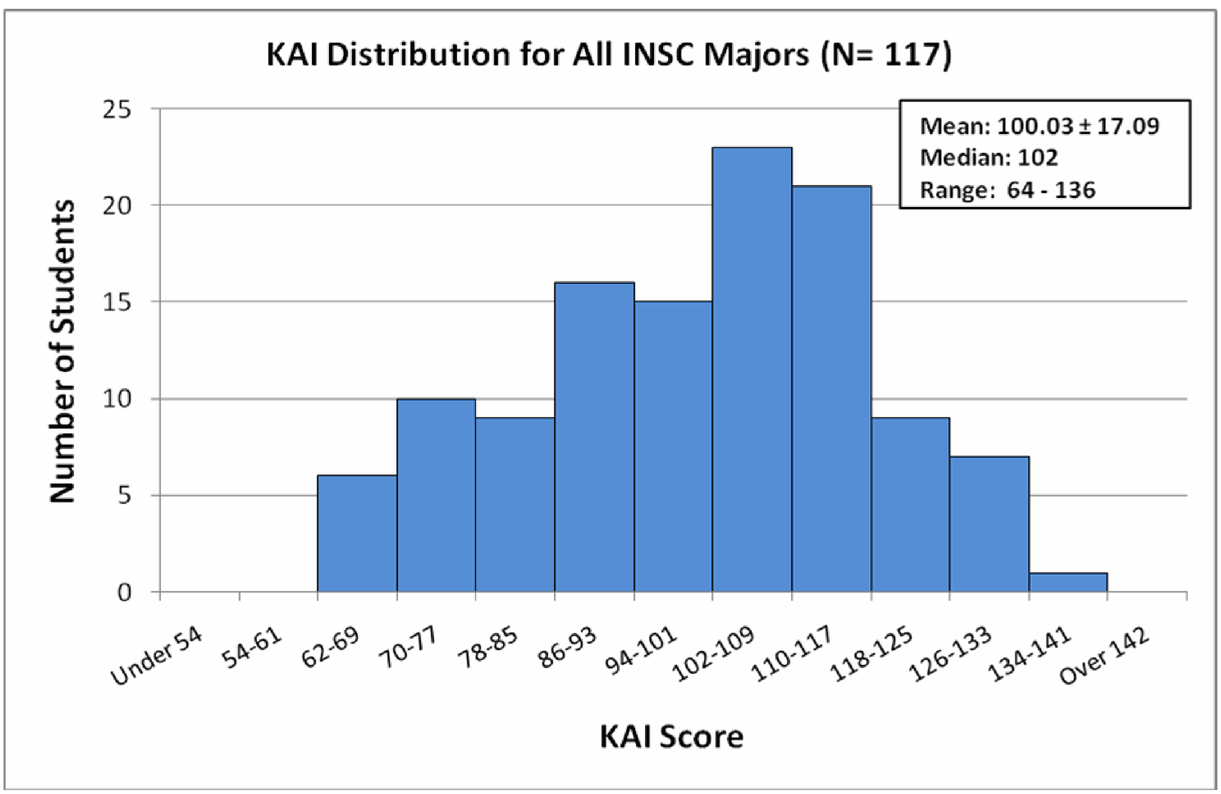

Figure 8: KAI score distribution for Information Science students

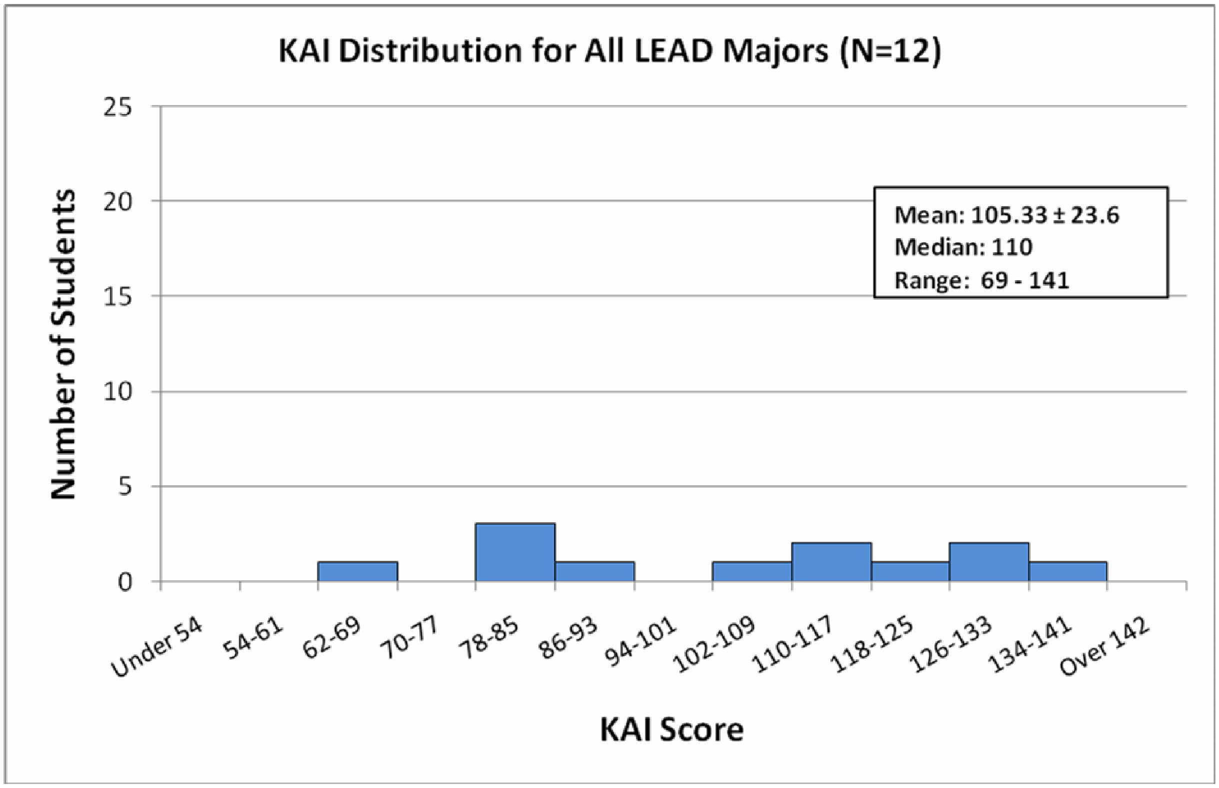

Figure 9: KAI score distribution for Leadership Development students

As expected (based on the general independence of level and style), a wide range of styles is present in each disciplinary sample: i.e., style is not correlated to type of domain knowledge. However, as Table 3 shows, the means of the sub-groups increase steadily as we move from Systems Engineering (mean of 95.19) to Software Engineering (mean of 97.33), Information Science (mean of 100.03), and Leadership Development (mean of 105.33), respectively[‡]. Median scores exhibit a similar increasing pattern. Is this trend significant, and if so, what does it mean?

Although the only statistically significant difference in means occurred between the Systems Engineering and Information Science samples[§], the overall trend in means invites consideration. Previous research indicates that occupational groups (e.g., teachers, engineers, bankers, nurses) and functionally-specialized groups within a particular occupation (e.g., production, design, and R&D – all within engineering) often have stable style distributions that are predictably different from those of the general population and each other[19]; the means of these groups correspond generally to the style "nature" of the bulk of the problems they face. In particular, groups that solve most of their problems *within one major conceptual or organizational structure* (e.g., technical paradigm, operational standard) tend to be more Adaptive (regardless of the size and complexity of that structure – these would be indicators of level, not style), while groups that *span several conceptual or organizational structures* as they develop and implement solutions tend to be more Innovative.

‡ Note: for undeclared majors (N=24), the range of scores was 61-117, with a median of 97, a mean of 94.25, and a standard deviation of 16.54.

§ ANOVA single factor analysis ($\alpha = 0.05$); $p = 0.030$

Recalling that the just-noticeable-difference (JND) in KAI group means is 5 points, and noting the differences in group means between our samples in Table 3, we are lead to ponder whether this trend might be predictable based on the problems faced by practitioners in the above-mentioned fields (and the ways in which those problems differ). Are the problems faced by Systems Engineers, for example, generally more tightly focused within one major conceptual structure than those faced by Information Scientists, leading individuals who are (as a group) slightly more Adaptive to pursue Systems Engineering? Does the fact that the curriculum for the Information Science degree (as defined at our institution) contains both Engineering and Management courses come into play, representing the spanning of two conceptual structures (disciplines, in this case) and attracting a slightly more Innovative group of applicants as a result? Furthermore, while the number of Leadership Development students is too small (N=12) to reach any definite conclusions, the corresponding mean is in the expected place in the progressing pattern, considering the multi-disciplinary nature of the degree and its relative uniqueness, even within the Management field[**].

In summary: if they are stable, then mean style differences in the distributions of practitioners of different disciplines (or sub-disciplines) could have interesting implications for recruitment to those various fields, practice within them, and for the instructional design of courses and curricula within their respective academic programs. These areas of interest (and related questions) require further investigation and will form the backdrop for future research.

Correlations between Cognitive Style and Performance

In considering the cognitive diversity of engineering students and the distinction between level and style, it is natural to ask whether students with particular styles are more successful in the classroom than others. A-I theory predicts that this will not be the case *in general*, although a student with some particular style may have an advantage in certain, specific situations (i.e., those in which that particular style is the most effective for resolving the given problem or sub-problem). In other words, while we expect to find students at all levels (both type and degree) within a particular style, and students of all different styles (from highly Adaptive to highly Innovative) operating at the same level, when faced with a particular problem, students whose respective levels and styles are the best match for that problem are more likely to succeed.

With these factors in mind, we examined the relationship between A-I style and cumulative grade point average (GPA) within our sample. As expected from A-I theory and other general studies[19], there was no correlation between KAI score and cumulative GPA ($r = -0.10$). When viewed at a glance, these results may seem in conflict with the work of O'Brien, et al.[25, 26] (as one example), in which students of different psychological types (as measured using MBTI) performed better (or worse) than others. However, when we consider that O'Brien's work focused on a single course within an entire curriculum, an explanation for this seeming contradiction becomes clear. Within any <u>one</u> course, the expectations and requirements for success are more likely to be a direct reflection of the particular instructor (i.e., the particular "problem" at hand is to satisfy *one specific* person), while cumulative GPA reflects performance over a (generally broad) range of courses of different types and with different instructors, making both results consistent with theory.

[**] It is also interesting to note that the range of scores was still large (72 points) even within this small sub-group.

Summary of Our Findings and Some Practical Implications

As a brief review of our key findings, we offer the following summary:

1. A wide diversity of A-I cognitive style was observed across the total sample of students and across sub-groups separated by gender, ethnicity, and academic major, respectively.
2. Taken as a whole, the female sample showed a slight skew in cognitive style towards Innovation when compared with the general female population. The male sample was in line with the general male population.
3. A trend in style means was observed among the groups separated by academic major, with group means increasing from Systems Engineering to Software Engineering, Information Science, and Leadership Development.
4. No correlation was found between cognitive style and cumulative GPA.

Separately and taken together, these findings support and illustrate the level-style distinction within cognitive diversity in general and in the context of engineering education. Now, to extend the brief comments we made in earlier sections of this paper, we will consider some practical implications of these findings, as well as the general importance of distinguishing between style and level in engineering education and practice. In particular, we will focus our attention on course design and delivery, as well as the formation and management of engineering teams.

Accommodating Cognitive Diversity in Course Design and Delivery

Theoretically, there is a range of possibilities available when we attempt to accommodate cognitive diversity in the classroom, from taking <u>every</u> student's cognitive style and level into account *individually*, to ignoring this diversity completely. Research suggests that educational outcomes are improved when instructor and student are matched in terms of style[2,9,10,11], while level differences between instructor/instruction and student are expected (otherwise, there would be little need for instruction!). Our study demonstrates how unlikely it is that an A-I style match will occur for more than a few students at a time in any particular course. From our findings, we know that the range of A-I style within our student population is wide, while the instructor represents a single point somewhere along the same style continuum.

On the other hand, trying to match the "style" of course materials to <u>every</u> student in the classroom individually would present an untenable logistical problem for the instructor; preparing many different versions of the same instructional materials (based on style) simply is not a viable solution overall. In addition, we recall that a diversity of approaches to problem solving is needed to solve a diversity of problems. Hence, *in general* (as we stated earlier), no one style is better (or worse) than any other, and it behooves us (as engineers) to be able to act in ways that are different from our preferences when the problem requires it. Kirton calls this *coping behavior*[19], and while everyone is capable of coping, this behavior comes at an extra cost (additional energy). Coping is also learned, which takes us back into the realm of the classroom. Since one aim of engineering education is to help students become better problem solvers, it makes sense to help them develop coping behaviors that are appropriate for different problem-solving circumstances; in that case, ensuring that every student (and every instructor) is "comfortable" (in terms of style) at all times would be defeating our own purpose.

So, where is the happy medium? Perhaps some general recommendations, well applied, will be the best and most practical way forward. Based on sound theory and personal experience, we offer the following suggestions:

Recommendation #1: First, cognitive diversity must be acknowledged, accepted, and valued in the classroom – both by instructors and students. While these statements may seem obvious, they bear repeating: we cannot assume that every student thinks as we do (as individual instructors), nor should we expect every student to do so – at least, not permanently (remembering coping behavior). Students do need to recognize that coping may be necessary at times in the learning environment, just as we need to recognize that there will be times when a student's approach – though different from ours – may have the greater value. To aid in this understanding, we highly recommend that instructors integrate (or at least encourage) relevant discussions of cognitive diversity into their classrooms, so students will have a better understanding of *why* they find some activities/assignments/learning techniques more (or less) comfortable, as well as *when* and *why* coping behavior may be necessary as they learn and practice in their discipline (and when different kinds of coping are required).

Recommendation #2: In acknowledging cognitive diversity, it is critical that the distinction between (and independence of) level and style is made clear. Otherwise, both students and instructors may fall into the trap of interpreting differences in style as differences in level and the owners of those differences (and their contributions) as inferior. Without an understanding of cognitive diversity and its value, a more Innovative instructor may, for example, misjudge the ideas of a more Adaptive student as "trivial" or "mundane", when they are actually important and high-level refinements of an existing system. Or, a more Adaptive instructor may criticize the contributions of a more Innovative student as "irrelevant" or "unfocused", when in fact they bring attention to some critical precipitating event on the horizon. These principles require attention in the classroom and in engineering practice, where engineers and their managers can make similar mistakes in judging one another's work.

Recommendation #3: When developing supporting course materials for students (e.g., syllabi, readings, web sites), instructors should strive for a degree of structure that will support the more Adaptive students in the classroom – that is, provide (but not necessarily ask for) the amount of structure that suits the more Adaptive extreme. While this may seem counterintuitive or (at least) counter to the notion that "all students should be equally accommodated in the classroom", in practice (as we have observed), this strategy works very well. True to their nature, the more Adaptive students appreciate the "extra" structure and make good use of it, while the more Innovative students tend to shed the structure they find "unnecessary" and make good use of the rest (which they too appreciate!).

Recommendation #4: When creating assignments and activities (i.e., when asking for materials from students), consider creating some assignments (or tasks within them) that are amenable to the more Innovative, and others that appeal to the more Adaptive. This not only gives each student some assignments that are best solved using his/her preferred style, but it also encourages them to work in non-preferred ways, increasing their coping skills and problem solving assets overall. Instructors should also consider style in the grading of assignments: in particular, it may be useful to consider how much structure is actually required in order to solve a particular problem vs. the amount of structure you (as the instructor) prefer. It can be difficult to evaluate the solutions of others in a way that is truly objective with respect to style, but if we are to advocate the understanding and appreciation of cognitive diversity, we must be prepared to set the right example from the start.

Implications for Collaborative (Team) Problem Solving

One of the most important implications of cognitive diversity arises when students need to collaborate (e.g., in project work, team assignments, etc.). While Adaption-Innovation theory cannot predict whether a student prefers working in groups, it can help explain the relative sensitivity to and importance of group consensus and adherence to group rules among students of different cognitive styles. As we noted earlier, more Adaptive students prefer to solve problems using more structure, with more of that structure consensually agreed; this includes social structure. Hence, a more Adaptive student will demonstrate a preference for working *within* the structures established by the team (e.g., timelines, task assignments, problem definitions, "group rules") and a greater desire for consensus. The more Innovative students are likely to be less concerned with these matters, preferring to solve problems using less structure, and therefore, being less concerned about (but not totally insensitive to) consensus and the adherence to rules or guidelines set up by the team (as forms of structure).

Hence, in general, heterogeneous teams (in terms of style) are more difficult to manage and typically have a more difficult time collaborating, unless they have learned how to manage their diversity well (which may include considerable coping behavior on the parts of some team members)[3,21]. Homogeneous teams can also fail, of course, but as Hammerschmidt demonstrated[13], such failure is more likely to be the result of a mismatch between the team's resources of level and style and those required by the problem, rather than interpersonal conflict within the team. This is not to suggest, however, that teams should regularly be designed to contain students with similar cognitive styles – nor should highly heterogeneous teams be formed for every project per se. Ideally, the composition of a team should match (as closely as possible) *the requirements of the problem* in terms of level and style, always remembering that complex problems tend to be "moving targets"[19]. A wider diversity of cognitive style and level increases the chance of effective problem solving over a wide range of problems – if it can be managed well.

In any case, we suggest that teams function more effectively if they understand A-I theory and the impact of cognitive diversity when working with others, and this has been born out in a number of contexts[3,5,13,15,19]. This familiarity reduces the tendency of students to view peers with different styles as being inferior in some way (i.e., to confuse style with level). Anecdotally, our students report that where they once may have viewed a team member with a noticeably different A-I style in a negative way, awareness of cognitive style and their relative positions along the A-I style continuum enabled them to value and harness their respective differences for a more effective problem solving experience. We intend to continue our investigation of the impact of A-I awareness in collaborative problem solving in our future research.

Conclusions and Future Work

Our exploration of cognitive diversity from a problem solving perspective confirmed our expectation that engineers exhibit a wide range of cognitive styles across genders, ethnic groups, and academic majors, as well as the fact that students of different styles are just as likely to succeed within our degree programs. Our findings also support the level-style distinction in problem solving and highlight the need for both student and instructor awareness of cognitive diversity in order to avoid the creation of interpersonal conflicts that distract students and instructors alike from their main learning objectives.

Even with these useful findings, a good deal of work remains to be done. One of the most obvious directions for future research is an exploration of cognitive gaps (i.e., gaps in level and/or style)[15,19] between individual instructors and their students, and the impact of those gaps on the educational experience, including student and instructor perceptions of each other, classroom management, and student performance in particular courses. In addition, our department has recently embarked on the development of an on-line degree program, in which student cohorts will complete an on-line version of the same course used here for the collection of KAI style data. In the very near future, therefore, we will be able to compare the cognitive diversity profiles of students who enroll in on-line degrees versus those who enroll in resident programs. We also intend to explore (through on-line activity tracking) differences in the use and responses of students of different cognitive styles to various modes of content delivery and on-line learning mechanisms (e.g., discussion forums, group assignments, on-line exams).

In general, cognitive style describes the preferred way a person seeks to bring about change, including the solution of problems. Most (if not all) human activity involves solving problems, from the simple (e.g., which sensory data should be attended to, and which should be ignored?) to the complex (e.g., how do we revive the global economy?). Even a basic familiarity with A-I theory can help instructors understand differences in their students and their responses to different classroom environments and instructional practices as they solve problems – alone and in teams. As we noted at the outset: the more we understand our students and ourselves, the better we can meet their learning needs and the greater (we hope) their learning will be. Awareness of cognitive diversity is one more way instructors can improve their pedagogy.

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