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Design Scenarios as an Assessment of Adaptive Expertise*

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The ability to adapt to new challenges is critical to success in rapidly advancing fields. However, educators and researchers struggle with how to measure and teach for adaptive expertise. This study used a design scenario to assess how undergraduates approach novel design challenges. A scenario presents individual students with a short realistic description of a complex, open-ended design problem. In this study, we developed a scenario from a cardiologist's concerns about the design of an implantable defibrillator. Participants included 63 senior design students and 37 freshmen enrolled in a signal analysis course. After reading the scenario, students responded to three questions: What do you need to do to test the doctor's hypothesis? What questions do you have for the doctor? and, How confident are you in your response? The first question tapped students' efficiency or their ability to devise an appropriate response. The second tapped students' innovation or their ability to consider important facets of the problem. The third question estimated students' confidence/cautiousness. Data were collected at the beginning and end of one semester. Analysis showed that seniors consistently devised more efficient and innovative solutions than did freshmen. Seniors were also more confident in their problem-solving abilities. Over time, all students became more innovative and more confident. Findings are discussed in terms of what they suggest about undergraduates' intellectual development at entry to and exit from a standard four-year curriculum and how adaptive expertise might be assessed within the context of students' regular academic coursework.

Keywords: adaptive expertise; efficiency; innovation; design.

INTRODUCTION

EXPERTS ARE EFFICIENT problem-solvers; they appropriately apply their understanding, and they have a depth of understanding that makes difficult problems tractable [1]. However, not all experts are created equal. Hatano and Inagaki [2] have identified two kinds of experts: routine experts and adaptive. Routine experts are efficient and technically proficient; however, they may fail to adapt when new types of problems develop [3]. Adaptive experts possess content knowledge and technical proficiency similar to that of routine experts, but they differ in important ways. Adaptive experts use different representations and methods to solve problems; they seek out opportunities for new learning in their field of expertise, successfully monitor their understanding, and conceive of knowledge as dynamic rather than static [1, 4, 5]. These methods and attitudes allow adaptive experts to act flexibly in novel situations [1, 2].

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The ability to adapt to new challenges and problems is critical to success in rapidly advancing fields. One growing professional field is biomedical engineering design, which involves solving open-ended problems under conditions of uncertainty and risk. For example, design products include pediatric ventilators, components for surgical procedures, and laboratory equipment. Given its demand for flexible problem-solving skills, the field of biomedical engineering design is an ideal arena in which to study the phenomenon of adaptive expertise [2].

A significant challenge to researchers interested in adaptive expertise is establishing valid and reliable ways of capturing and representing what people know, how they apply their skills, and how their performance varies over time and across problems. Recently, Schwartz, Bransford and Sears [6] have articulated several dimensions of adaptive problem-solving that lend themselves to empirical study (see Fig. 1). One dimension is efficiency. A second dimension is innovation. A third attitudinal dimension is an appropriate level of confidence.

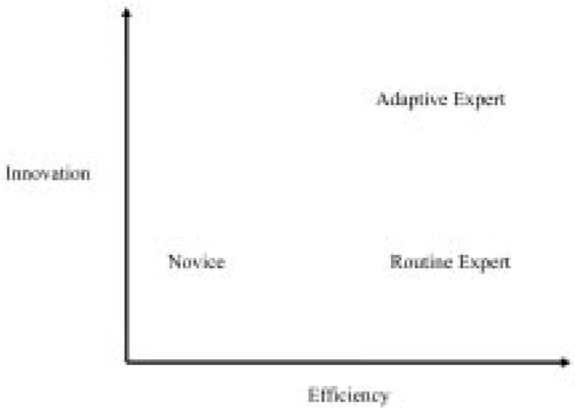

Fig. 1. Dimensions of adaptive problem-solving identified by Schwartz, Bransford and Sears (in press).

EFFICIENCY

Efficiency is a common metric of expertise and is often defined as the ability to retrieve and apply appropriate skills and knowledge [1]. Efficiency can also be defined in terms of consistency and accuracy [6]. For instance, expert physicians can reliably, quickly and accurately diagnose and treat a patient's complaint. Similarly, in the context of engineering design, efficiency can be defined as the ability to devise appropriate strategies for addressing a problem. In fact, when people think of engineering, efficiency is likely the first dimension to come to mind. This is because engineers often focus on computation and the derivation of accurate solutions.

Developmental differences have been observed in students' ability to derive efficient solutions to design challenges. For instance, when asked to define the design process, beginning design students rarely engaged in iterative processes such as evaluation and revision [7]. By contrast, more advanced students tended to progress to later stages of the design process including decision-making and project realization, and to continually evaluate the appropriateness of their decisions [8, 9]. Taken as a whole, this work suggests that beginning design students are not as efficient or able to devise a complete, working solution as their more advanced peers.

INNOVATION

Innovation is a less well understood facet of expertise. Yet, understanding innovation is critical to understanding routine vs. adaptive expertise. Innovation is related to efficiency in that it involves drawing appropriately on prior knowledge. Innovation differs from efficiency in that it requires the ability to recognize and then break away from routine approaches. In the context of engineering design, innovation can be defined as the ability to stop and consider a problem from multiple vantage points rather than foreclosing on a more immediate and smaller set of possibilities.

For instance, expert designers tend to take a breadth-first approach in which varied approaches are considered [10, 11]. By contrast, students tend to do little exploration and elaboration of the design space, often 'getting stuck' modeling a single alternative solution rather than considering multiple options [9]. Novices' limited perspective-taking also appears in their tendency to design for themselves rather than considering the needs and constraints of the user, and in their limited attention to contextual factors, such as safety concerns and the marketplace [7, 8, 12]. Taken as a whole, this work demonstrates that novice designers are not as innovative or do not define problems as carefully and elaborately as do experts.

CONFIDENCE

In addition to knowledge and skills, attitudes and beliefs are important to adaptive problem-solving [3]. One important attitudinal variable is confidence. As noted by Bandura [13], confidence can be a protective factor in the face of adversity and challenge; however, confidence can be debilitating when it is not aligned with actual competence. Thus, an important affective dimension of adaptive expertise is high caution coupled with high confidence [6]. Balance between the two is likely important because it sustains persistence, and supports the ability to model problems from multiple perspectives and 'let go' of assumptions that may interfere with innovation. For instance, in the field of engineering design, tentative confidence is likely to support a designer's determination to create novel but safe and effective products.

In sum, assessments of expertise in engineering design have been useful in identifying patterns in students' thinking, some of which may interfere with their ability to enter the professional design community. However, this literature is limited. First, the methods used are time-consuming and do not lend themselves well to use by educators, nor do they provide students with much feedback about their professional development. The findings reported here, for instance, were derived from detailed analysis of think-aloud protocols during problem-solving and observations of design activities in situ [7–11]. Moreover, design performance has not been explicitly examined via theoretical models of adaptive problem-solving [cf. 8]. This study addressed these limitations. To our knowledge, it is one of the first efforts to bridge research in design cognition and design education to the construct of adaptive expertise [2]. Second, it tested the utility of one 'education-friendly' tool for comparing students' approaches to design challenges: design scenarios.

DESIGN SCENARIOS AS A MEASURE OF ADAPTIVE EXPERTISE

Design scenarios present individual students with a short description of a realistic design

Signal Analysis Problem

Dr. Mark Wathen is a cardiologist experimenting with Implanted Cardiovertor Defibrillators (ICD) to continuously monitor heart rhythm for arrhythmias and to initiate interventions (shock) as needed. Dr. Wathen is concerned with the way current devices detect and treat the arrhythmias and needs a biomedical engineer like you to help out with the next generation design. Here is what Dr. Wathen has shared with us so far about the situation.

"What we know about the ICD is that it must first detect tachycardias and then treat them as they occur in real time in an automated fashion. This means that detection of arrhythmias is first based on heart rate. However, the devices really want to treat only Ventricular Tachycardias (VT) (arising from the ventricles) and not Supraventricular Tachycardias (SVT) (which arise from the atria). The former are life threatening and the latter not. The treatment delivered by the ICD is a shock: A LARGE and uncomfortable shock. Thus the device needs to distinguish VT from SVT. So, alternative techniques have developed to distinguish the two categories of tachycardia. All work to date has utilized recordings only from a single site in the ventricle. I am postulating that using two sites will permit differentiation of SVT from VT. Should this idea work out, it has great potential for changing the industry's reliance upon rate-based detection to some other form."

Fig. 2. Design scenario completed by first-year and fourth-year engineering students.

challenge and then ask them to describe how they would solve the problem. In developing our scenarios we had three goals in mind. First, we wanted to know if we could measure how adaptively undergraduates approach design problems. Specifically, we wanted to know if we could reliably assess the dimensions of efficiency and innovation. Second, we wanted to know if our measure was sensitive to changes in students' approaches over time. That is, would our measure distinguish people by their level of adaptive expertise (e.g. sort beginning from advanced engineering students)? Third, we wanted to gain an understanding of relations among efficiency, innovation and confidence as students acquire domain knowledge. Our overarching goal was to enhance understanding of students' reasoning about design and, in turn, use that understanding to create instruction that promotes the development of adaptive expertise.

In this study, we developed a scenario from information provided by a cardiologist at the Vanderbilt University Medical Center. The scenario is presented in Fig. 2. After reading the problem, we asked students to respond to the following questions: (1) What do you need to do to test the doctor's hypothesis? (2) What questions do you have for the doctor? and, (3) How confident are you in your response? The first question was designed to tap students' efficiency or their ability to devise an appropriate response to the problem statement. The second question was designed to tap students' innovation or their ability to consider a range of potentially important facets of the problem. The third question was intended to estimate students' confidence/cautiousness.

HYPOTHESES

We expected that, relative to beginning engineering students, advanced students would: 1) generate more efficient solutions (i.e. generate a greater number of more complex and accurate strategies for testing the doctor's hypothesis), 2) demonstrate more innovative thinking (i.e. pose a greater number and variety of questions about the problem), and 3) have higher levels of confidence. Over time, we expected that both beginning and advanced students would increase in their efficiency, innovation and confidence. Correlations among confidence and efficiency and innovation were an open question.

We also expected our results to reflect differences in course content. Put another way, we expected to find differences in the form and the substance of students' thinking based on their current educational experiences. Specifically, we expected students who were learning about the phenomenon of cardiac signal analysis to generate more questions about the heart, etc. By contrast, we expected students whose coursework was focused on design to pose questions pertaining to the design process (e.g. customer needs, other approaches).

PARTICIPANTS

We piloted our measure with 37 students enrolled in two sections of an introductory-level engineering science course, and 63 students enrolled in a year-long senior design course. The introductory course is a one-hour credit class focused specifically on cardiac signal analysis; it is designed to complement the skills and knowledge students acquire in a larger 3-credit introduction to the engineering course. The year-long design course is a capstone experience in which students are expected to apply the skills and knowledge they have gained in the previous three years.

Students responded to the scenario at two time points, approximately four months apart. First-year students completed the problem as part of a pre- and post-test at the beginning and end of the fall semester 2003. Fourth-year students completed the problem electronically as a homework assignment during fall 2003 and spring 2004. Between assessments, fourth-year students were engaged in the process of developing a design project. Complete data was obtained for 28 freshmen (76% participation rate) and 39 seniors (62% participation rate).

ANALYSIS

We began our analysis by asking the two participating course instructors to create a scoring rubric which identified a potential range of student responses and classified them on a continuum from novice to expert (see Appendix A). For instance, in response to the first question, a student might offer the strategy 'gather data from 2 sites.' Given its simplicity, this strategy was categorized as a novice approach. By contrast, the more complex suggestion 'gather data from 1 site and compare it to 2 sites to see if 2 sites are necessary' was categorized as an expert-level strategy.

Instructors similarly identified the potential range of student questions and classified them as novice, proficient or expert. Novice questions focused on comprehension (e.g. 'What is ventricular tachycardia?'). Questions demonstrating problem-specific knowledge of cardiac signals (e.g. 'Can I see a tracing of the ECG?') were categorized as proficient. Questions that suggested a broader approach to the problem and an understanding of design (e.g. 'Why is this hypothesis the best one?' and 'What other approaches have people taken to this problem?') were categorized as expert.

The rubric was applied by two graduate students, blinded to time point and class membership. With regard to our first question, 'What do you need to do to test the doctor's hypothesis?', our raters counted the number of strategies generated by students and evaluated each response as novice or expert (novice strategies received a rating of 1; expert strategies received a rating of 2). These coders also rated the student's overall solution in terms of its accuracy (inaccurate strategies = 0, somewhat accurate = .50, completely accurate = 1). For our second question, 'What questions do you have for the doctor?', our coders counted the number of questions, and then rated each response as novice, proficient or expert. Novice questions received a score of 1, proficient a score of 2, expert questions a score of 3. Inter-rater reliability on these measures was acceptable: number of strategies > .89; quality of strategies range = .52–.81; accuracy of strategies > .68; number of questions > .88; quality of questions, range = .52–1.00. The number of strategies and questions students could generate was not limited.

We then used these data to form the efficiency and innovation variables. The efficiency variable was derived as the sum of the quality of students' strategies divided by the number of strategies generated. For instance, a student who generated one novice strategy and one expert strategy would receive a summary score of 3; this score was then divided by the total number of strategies generated, which was 2. The innovation variable was similarly derived: the sum of the quality of students' questions was divided by the number of questions posed. The confidence variable was derived from student ratings, which were made on a 5-point scale (1 = not at all confident, 5 = very confident).

One-way repeated measures analysis of variance (ANOVA) were used to test for effects for time, year and time by year interactions. To enhance our understanding of relations among theoretically important dimensions of adaptive expertise, correlations among efficiency, innovation and confidence were calculated for each group at each time point. Descriptive statistics for all study variables are summarized in Table 1. Figure 3 is a graphic representation of results for efficiency and innovation by time and by age group.

Consistent with our hypothesis, fourth-years generated more efficient solutions than did first-years (main effect for year, $F[1, 64] = 59.96$, $p < .000$, $eta^2 = .49$). The number of strategies suggested by fourth-year students ranged from 0–3 on the pre- and post-tests. The number of strategies suggested by first-year students ranged from 0–2 on the pre- and post-tests. Fourth-year students also took a more innovative approach than did first-years and all students were more innovative on the post-test (main effect for year, $F [1, 65] = 17.09$, $p < .000$, $eta^2 = .21$; main effect for time, $F [1, 65] = 10.99$, $p < .000$, $eta^2 = .15$). The number of questions posed by fourth-year students ranged from 0–4 on the pre-test and 0–6 on the post-test. The number of questions posed by first-year students ranged from 0–2 on the pre-test and 0–3 on the post-test. Accuracy ratings for both groups ranged from 0–1 on the pre- and post-tests.

As expected, fourth-year students were more confident and both groups' confidence increased over time (main effect for year, $F[1, 65] = 90.35$, $p < .000$, $eta^2 = .58$; main effect for time, $F[1, 65] = 146.34$, $p < .000$, $eta^2 = .69$). We also found a small

Table 1. Descriptive statistics for student efficiency, innovation and confidence by year and by time

Efficiency	Pre Mean	SD	Post Mean	SD
First-year	.46	.73	.88	.91
Fourth-year	1.86	.94	1.94	.95
Innovation				
First-year	.83	.72	1.32	.84
Fourth-year	1.56	.80	1.80	.57
Confidence				
First-year	1.46	.88	4.53	1.71
Fourth-year	5.00	1.75	7.18	1.68

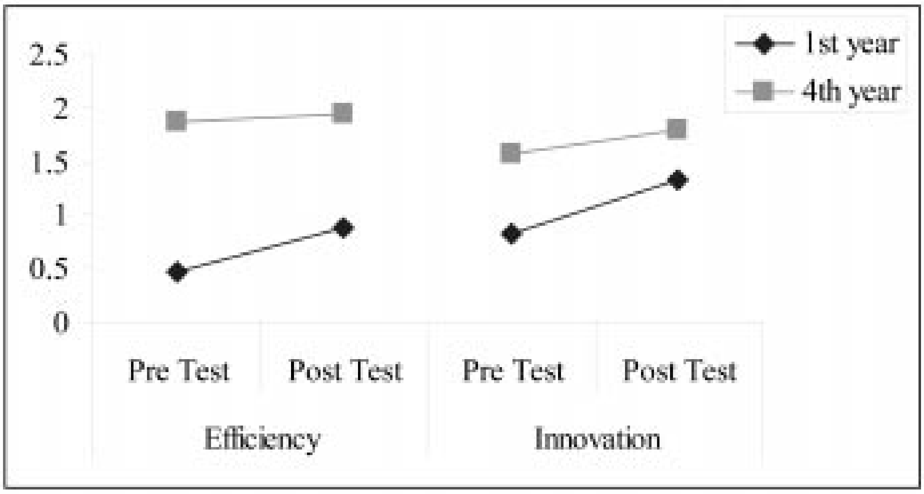

Fig. 3. Efficiency and innovation by year and by time.

time by year interaction; first-years had larger gains than did seniors ($F[1, 65] = 4.22$, $p < .05$, $eta^2 = .06$). Confidence ratings for fourth-years ranged from 1–4 on the pre-test and 2–5 on the post-test. For first-years, confidence ranged from 1–5 on the pre- and post-tests.

To test our hypothesis that students' approaches would reflect their educational experiences, we examined the proportion of novice, proficient and expert questions posed by each group at each time point. Fourth-year students asked more novice, proficient and expert-level questions at both time points (main effects for year: Novice, $F[1, 65] = 12.20$, $p < .001$, $eta^2 = .16$; Proficient, $F[1, 65] = 16.10$, $p < .00$, $eta^2 = .20$; Expert, $F[1,65] = 15.69$, $p < .000$, $eta^2 = 19$). Consistent with their course experiences, first-year students made the largest gains in proficient-level questions (main effect for time, $F[1, 65] = 13.61$, $p < .001$, $eta^2 = .17$). Both groups of students asked more expert questions on the post-test (main effect for time, $F[1, 65] = 6.76$, $p < .01$, $eta^2 = .09$).

Finally, we examined relations among efficiency, innovation and confidence. Table 2 summarizes these relations by year and by time point. For fourth-year students, we found consistent positive links between confidence and innovation, and a moderate correlation between efficiency and innovation on the pre-test. By contrast, first-year students' confidence was related only to efficiency on the pre-test; a correlation between efficiency and innovation on the post-test approached significance.

DISCUSSION

This study was designed with two purposes: 1) to bridge research in design cognition and design education to the construct of adaptive expertise, and 2) to test the utility of one 'education-friendly' tool for comparing students' approaches to realistic design challenges. Specifically, we developed and used design scenarios to assess three dimensions of adaptive problem-solving among beginning and advanced engineering undergraduates. The three dimensions are efficiency (i.e. generating accurate problem-solving strategies), innovation (i.e. problem-scoping or elaborating on a problem statement) and confidence.

Consistent with other investigations of undergraduates' reasoning about engineering design [e.g. 7–9], fourth-year students devised more efficient and innovative solutions than did first-years. Fourth-year students were also more confident in their problem-solving abilities. Over time, all students became more innovative and more confident. As expected, much of the increase in innovation for beginning students appeared related to their course experience and greater understanding

Table 2. Correlations among all study variables by year and by time

First-years Pre-Test	Confidence	Efficiency	Fourth-years Pre-Test	Confidence	Efficiency
Efficiency	.66**		Efficiency	.40*	
Innovation	.24	.11	Innovation	.39*	.39*
Post-Test			Post-Test		
Efficiency	–.29		Efficiency	–.01	
Innovation	–.20	$.36^+$	Innovation	.36*	.14

* = p < .05; ** = p < .01; + = p < .06.

of cardiac signal analysis. That is, this group of students was able to generate more questions related to the phenomenon of cardiac signals. By contrast, increases in innovation for advanced students suggested a greater tendency to take a 'breadth-first approach;' on the post-test these students asked questions across a spectrum of issues including basic vocabulary, questions about cardiac phenomena, and awareness of broader design issues, including others' approaches to similar problems. Advanced students were also more likely to question the problem statement as given. This is consistent with evidence that adaptive designers take the client's wishes and demands as a starting-point rather than absolute law [1].

We were also interested in relations among the dimensions of efficiency, innovation and confidence. Given our definitions we might expect that the quality of students' innovation (i.e. elaboration on a problem statement) would be positively related to their efficiency (i.e. actions taken to solve the problem). This is because students who consider the problem from multiple vantage points gain a deeper understanding and, in turn, generate more effective problem-solving strategies. Correlations between efficiency and innovation did not support this expectation. However, consistent with current thinking that tentative confidence underlies innovation [6], positive links were found between advanced students' innovation and confidence at both time points. No such links were found for beginning students.

This study represents a promising avenue for assessing adaptive expertise within the context of students' regular academic coursework. However, several outstanding questions remain. For instance, what is an appropriate level of confidence? How do our students compare to experts? We are currently addressing these issues by collecting responses to this scenario from a pool of design experts who do and do not have expertise in the area of cardiac phenomena. Grounded in research in the domain-specific and domain-generality of expertise [14, 15], this approach may enhance understanding of adaptive problem-solving by establishing 'benchmarks' when domain-specific knowledge is high and when it is not.

Another concern relates to the fact that, while our measure taps the separable dimensions of efficiency and innovation, it does not necessarily allow students much 'room' on the efficiency dimension. For this reason we are currently developing a set of design scenarios that prompt students to go beyond generating problem-solving strategies to actually enacting a solution. We are also interested in developing problem-solving resources to accompany the scenarios. Such resources may allow us to observe how students move between the dimensions of efficiency and innovation (i.e. how they use their ability to define the problem to generate testable solutions and, in turn, how new questions emerge from testing their ideas). To learn more about the role of problem-specific knowledge we are currently replicating the study, assessing both groups' knowledge of cardiac signal analysis.

Finally, our design challenge is realistic; however, the way students complete it is not. In 'the real world' most design problems are taken on by teams rather than individuals. For this reason we also want to explore the quality of solutions derived by individuals and by teams. We also see opportunities for using the design scenarios as a teaching tool. For instance, students could complete the scenario in class (as individuals or in groups) and then compare their solutions to their peers and to the solution of an expert. Repeatedly engaging in such activities may increase students' awareness of and ability to reason about design issues that transcend the specific content of a problem.

In sum, our work suggests that design scenarios can reliably and sensitively measure dimensions of adaptive expertise in engineering design, which is an important contribution to research on adaptive expertise and to the field of engineering education.

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APPENDIX A. SCORING RUBRIC FOR SIGNAL ANALYSIS PROBLEM

1. What do you need to do to test the doctor's hypothesis?
   - Novice
     Gather data from 2 sites
     Use multiple humans/patients
   - Expert
     Compare data from 2 sites to data obtained from 1 site to see if 1 site would have been sufficient
     Conduct non-human testing: animal or computer simulations
2. At this time, what questions do you have for the doctor?
   - Novice
     Questions about vocabulary (e.g. what is SVT?)
     What are the sites that you plan to sample from?
   - Proficient
     Can I see a tracing of what the ECG looks like?
     Will I be able to compare timing and voltages of ECG?
     How is the root cause manifested in the physiology?
   - Expert
     What kind of literature is available on this subject?
     What kind of team or resources is available (equipment, money, personnel)?
     Why is this hypothesis the best one? Why this solution?

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