The Dissertation Committee for Stephanie Dawn Rivale Certifies that this is the approved version of the following dissertation:

AN EXPERT STUDY IN HEAT TRANSFER

Committee:

Taylor Martin, Supervisor

Tony Petrosino

Walter Stroup

Jill Marshall

Kenneth R. Diller

AN EXPERT STUDY IN HEAT TRANSFER

by

Stephanie Dawn Rivale, B.S.; M.S.

Dissertation

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

The University of Texas at Austin

May 2010

Dedication

To Shanon because she always inspired me to be better and do more.

Acknowledgements

I have had so many mentors and supporters along the way that I cannot say thank you loud enough. First, I need to acknowledge my family who put up with me while I was having my dissertation; especially my parents whose support, confidence, and can do attitude helped me get here in the first place. They shaped me into a strong independent woman not afraid to go places and take on new challenges. Their love and support have always been constant and unconditional. My sister Shanon continues to inspire me to be better at everything I do. I owe Stacy and her family a big thank you for graciously enduring my absence through my extended dissertation process. I will be a better Tia once this chapter is finally closed.

Jessica Pierson has been a true friend, intellectually generous, and taught me how to truly engage in the work and ideas of others. This last skill I will take with me always. Sherylanne and Eric were my eternal support throughout the process even if they weren’t in the same zip code. They supported all the successes and the tears.

I could not have made it without the support of my two writing groups. The original Writing Blocks was a wonderful experience; thank you Luz, Stephanie, and Jessica. Part II was there through the grueling end and read many crappy first drafts and let me think out loud. Teddy has been such a great cheerleader (and football buddy); he has both great ears and an enormous heart. Brian Fortney has been a life saver; I won't ever be able to repay his kindness and support. Steven and Shelley made the best thinking partners. I have benefited tremendously from Shelley's many years of experience as a true Master Teacher. Alma de Mujer and the Taco 5 came into my life and my dissertation when it was nearly at a breaking point. I am also indebted to the lab especially, Ayiesha who kept me company during the late nights in Sanchez when we had to outsmart the 10 pm lockdown, Sarah who always helped sort it out, Carmen who made it hard not to laugh or smile, and Tom who always had a kind word or an off the wall cattle prod story.

I am thankful to have heard the Gospel according Uri in my first semester at UT. He introduced me to nearly ever paper I've needed to know and helped me understand how to help foster success and diversity in STEM. He imparted the knowledge that continues to fuel the passion. Vicki Stratton, Jennifer Wagner, and Kathy Schmidt always made everything easier. Kathy also made the conferences on the beach much more enjoyable. I am grateful to Dr. Stroup whose Systemic Reform class fundamentally changed my thinking more than any other experience. It was the aha semester. It may have taken a while, but I've seen the brilliance in almost every rant. My committee has been very patient and supportive. I am indebted to Dr. Diller, the collaboration and the opportunity to observe his classroom helped teach me what it is supposed to look like. Tony Petrosino gave me excellent career advice and taught me how to conference and network well. Jill Marshall helped me navigate my way through the equity and the women in STEM literature and has been an exemplar model in student-centered teaching. And finally, my advisor Taylor Martin taught me how to design and conduct great educational research and has been patient as she tried to teach me her prolific ways.

There is also a long list of mentors who each had a hand in my opportunity to join the club. First, my science teacher Hugo Ferchau challenged me when no one else did. Beth Olivares and the McNair office were home when it was really thousands of miles away. Tom Windham taught me the true meaning of mentoring many years ago and has continued to be one through it all. Susan Solomon helped me see the promise in myself and encouraged me to stay an engineer. She was right, it has always paid better to do the same work. Sallye McKee helped me find my calling, a graduate program and branded the *each one teach one, each one reach* philosophy into my life. Jesus Trevino modeled inclusive excellence and taught me both how to build a coalition and how to slay vampires. Kathy Scherer helped me keep it all together and figure out what was hard and why.

Finally, to my new BOLD colleagues, thank you for giving me the time and space to finish. I am especially grateful to Jackie Sullivan for believing in me and going to bat from the beginning. I am thankful for the opportunity to apply my years of collective knowledge and experience to do the work of adding more color and women to the engineering pool. Because dreams need doing!

An Expert Study in Heat Transfer

Publication No._____________

Stephanie Dawn Rivale, PhD.

The University of Texas at Austin, 2010

Supervisor: Taylor Martin

This study compares engineering expert problem-solving on a highly constrained routine problem and an ill-defined complex problem. The participants (n=7) were recruited from two large public Research I institutions. Using a think aloud methodology, the experts solved both routine and non-routine problems. The protocols were transcribed and coded in *Atlas ti*. The first round of coding followed a grounded theory methodology, yielding interesting findings. Unprompted, the experts revealed a strong belief that the ill-defined problems are developmentally appropriate for PhD students while routine problems are more appropriate for undergraduate students. Additional rounds of coding were informed by previous problem solving studies in math and engineering. In general, this study confirmed the 5 Step Problem Solving Method used in previous challenged based instruction studies. There were observed differences based on problem type and background knowledge. The routine problem was more automatic and took significantly less time. The experts with higher amounts of background knowledge and experience were more likely to categorize the problems. The level of background knowledge was most apparent in the steps between conducting an overall energy balance and writing more problem specific relationships between the variables. These results are discussed in terms of their implications for improving undergraduate engineering education.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

Today's engineering graduates are faced with a more global and rapidly evolving world. Numerous reports, such as the *Engineer of 2020* and *Gathering Above the Rising Storm*, call for a transformation of engineering education that fosters the development of innovation while still maintaining high levels of technical proficiency (Augustine, 2005; Clough, 2005). Practicing engineers must constantly strengthen their knowledge base and become more efficient in applying it. As processes and industries rapidly evolve, they must use new and existing knowledge to solve novel and innovative problems. Traditional teaching methods in engineering education have focused on training students to efficiently solve routine, textbook-like problems but fail to prepare students to use their knowledge flexibly in novel situations. While these typical routine problems are common in the curriculum, they are not representative of the problems that they will encounter as practicing engineers. In a qualitative study of workplace engineering, Jonassen, Strobel, & Lee (2006) found that nearly all workplace problems are complex and ill-structured. Students often only encounter complex ill-defined problems at the end of their four year engineering program and enter the workforce without these critical skills requiring more on the job training.

How can we prepare students to solve these ill-defined complex problems that they will encounter as working engineers? The Vanderbilt-Northwestern-Texas-Harvard/MIT (VaNTH) Engineering Research Center attempted to answer this question in a Biomedical Engineering context. The VaNTH project designed a biotransport engineering curriculum to help students develop innovation and efficiency. Innovation was operationalized as the adaptive ability to perform well in novel and fluid situations, and efficiency was operationalized as the ability to appropriately apply their taxonomic knowledge in a timely manner. Schwartz, Bransford, and Sears (2005) have hypothesized that instruction that develops innovation and efficiency together will lead students to progress further along a trajectory toward adaptive expertise than instruction that teaches for efficiency first. This theory was tested explicitly in previous VaNTH projects conducted to explore the development of these two constructs. From these studies questions arose about what the endpoint looks like. How do experts solve these complex ill-defined problems?

There is a large body of literature on expertise and expert performance (reviewed in more detail in the following chapter). However, nearly all this research used routine problems and situations to quantify differences in novice and expert performances. These studies of expert performance on routine problems found that in addition to having a more complete knowledge base, experts are typically more adaptive and flexible in their thinking than most students. Experts' knowledge is organized around the big ideas of the field, whereas novices tend to think of domain knowledge as a large collection of equations. Experts differ in knowledge representation, general problem solving skills and approaches, and how and what details are perceived (Chi, Feltovich, & Glaser, 1981; Larkin, McDermott, Simon, & Simon, 1980). In problem solving, experts spend more time on understanding the problem and finding a useful representation based on key principles in the domain. Novices typically start by trying to find the correct equation based on surface features. While most expertise research was conducted using routine problems and situations, only limited research exists on expert performance in innovative situations (Raufaste, Eyrolle, & Marine, 1998; Schraagen, 1993; Schunn & Anderson, 1999).

This study will help fill this gap by addressing the following two research questions: (1) How do engineering experts solve non-routine complex problems? (2) Does an experts' process solving these types of non-routine engineering problems differ from the processes found in classic expertise research using routine textbook-like problems? Although the study was motivated by the desire to improve engineering education, it directly compares expert performance on two different types of problems. Engineering experts were asked to solve two heat transfer problems: a highly constrained textbook problem and a complex novel ill-constrained problem.

The previous VaNTH studies included both types of problems; the students solved a series of complex ill-constrained challenges, but routine problems were given as homework. During multiple iterations of the CBI Biotransport course, the working definition of innovation evolved. At the beginning of each challenge, students worked in groups to generate their own ideas about how to solve the challenge. Initially, students were producing lists or written explanations about their ideas of how to get started on the problem. This prompted the instructor, the domain expert on the project, to reflect on his own problem solving process. Students were then given explicit instruction a 5 step process adapted from the collaborating experts process: define the system, determine how this system interacts with the environment, identify the governing principles, identify the appropriate constitutive relationships and then solve the challenge. First, this method encouraged students to define the system or boundary for calculating inputs and outputs. After determining what aspects of the problem were included in the system, the next step they were instructed to identify how this system interacts with the surrounding environment. Since students often only see surface conditions of the problem and then jump straight to looking for the appropriate equations, they were required to identify what governing principles, such as the conservation of energy, apply to the problem and then identify the correct constitutive equations, such as the rate equations for conduction or convection. The final step is solving the problem using the identified constitutive equations and governing principles.

This 5 step expert problem solving was generated by *one* expert's process for solving both routine and ill-constrained problems. Will the engineering experts in this study use a similar process? Expert studies in mathematics have elicited a more general problem solving cycle (reviewed in more detail in the following chapter) that can be broken down into 4 cyclic steps: orienting, planning, executing and checking. (Carlson & Bloom, 2005) In addition to comparing expert performance on the different types of problems, the problem solving processes used by the experts will be analyzed and compared to those used in previous expert studies.

Classic expertise research studied two groups, experts and novice. More recent studies have included different kinds or groups of experts (Hmelo-Silver & Pfeffer, 2004; Raufaste, et al., 1998; Schraagen, 1993; Schunn & Anderson, 1999; Wineburg, 1997)

Study designs have included both task-experts and domain experts (Hmelo-Silver & Pfeffer, 2004; Raufaste, et al., 1998; Schraagen, 1993; Schunn & Anderson, 1999; Wineburg, 1997) This experimental design has helped to differentiate how experts use domain specific knowledge and general scientific reasoning skills and heuristics. Similarly, the experts in this study were selected to explore differences in engineering specialization and background knowledge. The two problems used in the study rely on heat transfer domain knowledge. The experts in this study have various levels of experience teaching and conducting research in heat transfer and its related transport domains.

In this study, seven engineering experts were asked to solve two different heat transfer problems: a routine problem and a more complex ill-defined problem. They were audio taped using a think aloud methodology. (Ericsson & Simon, 1993) These interviews were then transcribed and analyzed using a combination of grounded theory and protocol analysis to better understand the nature of expert engineering problem solving and whether the type of problem or experience/specialization of the expert will significantly affect the problem solving performance or process.

The following chapter reviews the literature on expertise and the verbal reporting methodologies used in other studies. Chapter 3 describes in more detail the participants, the problems used in the study, and the coding and analysis process. Chapter 4 explains the results from both the grounded theory analysis and the analysis informed from previous problem solving studies. Chapter 5 discusses the significance of the results found in this study and how these results can inform engineering education and curriculum reform.

Chapter 2: Literature Review

Modern expertise research began with the study of chess masters. Over a hundred years ago, Alfred Binet conducted the first blindfolded chess experiments to investigate the intellectual superiority of chess masters (Binet, 1893/1966; Ericsson, 2006b). In his doctoral thesis, de Groot (1965) continued the study of expertise using think aloud methods to study chess performance. The translation of his research and the artificial intelligence movement sparked many expert-novice studies in numerous domains. However in problem solving domains, most of this research used textbook-like problems to study expert and novice performance in routine situations. The recent emphasis on the development of innovation has sparked research focused on performance in innovative non-routine settings. In this chapter, I first review the classic research in expertise followed by more recent work in expertise in complex systems and adaptive novel situations. Then I explore the different methodologies used in previous expert studies. Then I review the problem solving literature that is relevant to this study.

CLASSIC EXPERTISE RESEARCH

Classic expertise research has made numerous contributions to our current understanding of how people learn. Experts' knowledge is organized around the big ideas, whereas novices tend to think of domain knowledge as a large collection of equations. (Chi, et al., 1981) In addition to having a more complete knowledge base, experts are typically more adaptive and flexible in their thinking than most novices. Experts differ in knowledge representation, general problem solving skills and approaches, and how and what details are perceived (Chi, et al., 1981; Larkin, et al., 1980). In problem solving, experts spend more time on understanding the problem and finding a useful representation based on key principles in the domain. Novices typically start by trying to find the correct equation based on surface features (Chi, et al., 1981). Table 2.1 summarizes what we have learned from classic expertise research. The following section expands on these key contributions.

Table 2.1: Summary of Classic Expertise Research

Attributes of Expertise	Reason	References	Reference Domain
Excel mainly in their own domains	Large amount of domain knowledge	Minsky & Papert (1974) Voss & Post (1988)	AI Political science problems by chemists
Perceive large meaningful patterns in their domain	Organization of knowledge (chunking) not superior ability	Reiter (1976) Egan & Schwartz (1979) Akin (1980) Lesgold et al. (1988)	GO Circuit Diagrams Architectural Plans X-rays
Fast and efficient	Practice and experience leads to automation and less cognitive effort	deGroot (1965) Klein (1993) Gentner (1988) Voss et al. (1983)	Chess Decision Making Typing Social science
Superior short-term and long-term memory	Chunking not innate capacity	Chase & Ericsson (1982)	Digit recall
Represent problem in a deeper (more principled) way	Organization of knowledge	Chi et al. (1981) Weiser & Shertz (1983)	Physics Programming
Spend time analyzing problem qualitatively	Time spent understanding and representing the problem	Paige & Simon (1966) Voss & Post (1988)	Algebra problem
Strong self-monitoring skills	More aware of what they know and what they need to know, check themselves	Simon & Simon (1978) Larkin (1983) Chi et al. (1981) Chi (1978) Miyake & Norman (1979)	Physics Physics Physics Chess Text recall

Chi et al.'s (1981) landmark expert novice study is the most cited publication in the field of cognitive science. This paper reported four experiments that used categorization methods to elicit differences in knowledge and problem solving. In the first experiment, both novices and experts were asked to sort 24 physics textbook problems each written on an index card. The novices were undergraduate students (n = 8), and the experts were advanced graduate students. The subjects first sorted the cards into categories. They were asked to re-sort the cards for consistency. Then the subjects were asked to explain why they categorized the problems what they did. The first and second sorts were consistent in both experts and novices, implying that the sort was based on some meaningful pattern or structure. The groups did differ in the time that they took to sort the problems; the experts took longer (18 minutes or 45 seconds per problem) than novices (12 minutes or 30 seconds per problem) in the first sort. However, experts took less time (4.6 minutes) than novices (5.5 minutes) on the second problem sort. Using cluster analysis they found that experts grouped problems based on underlying principles (even when surface features were different), and novices grouped solely on surface features. Examples of surface features are the actual physics vocabulary in problem, the look of the problem, or the relation between objects in a problem (block on inclined plane).

The second experiment examined the results of Study 1 more carefully. The researchers constructed a subset of the problems into pairs of problems that differed in deep structure (physics principles) but matched on surface structure (objects to be acted upon). Each problem pair contained the same surface feature such as an inclined plane, but differed in the general principle that governed the correct solution to the problem such as Newton's Force Laws or the general conservation principles. Novices and experts sorted the problems following the hypothesized explanation of Study 1.

In the third experiment, experts (n=2) and novices (n=2) received 20 terms generated by previous categorizations studies - a combination of terms generated by both novices and experts. They were asked to describe everything they could think of in 3 minutes about that term and about solving problems linked to that term. The authors created concept maps from these explanations. Experts' networks were centered on physics principles, such as Newton's Laws, and how these principles applied to the problems. Novices' networks focused on surface features, comparing and contrasting the different surface features in the problems.

In the fourth experiment, experts (n=2) and novices (n=2) were asked to give their "basic approach" to solving the 20 problems categorized in Study 2. The experts agreed most of the time. They stated the physics principle as the basic approach. The novices' responses varied more than the experts' responses. They either gave general get-going statements or they began solving the problem by explaining what equations they would use. Next the authors examined these basic approaches and how participants arrived at them. In a side study, they found that while novices and experts identified the same actual keywords in the problem as important to defining a basic approach, experts did different things with these features.

Personally, I think students learn the importance of these key terms from their experiences observing professors solve example problems during class lectures and doing many similar types of problems as homework. Although they have learned that these terms signify something important, they often do not really know what they mean, and if they do, the meaning is not connected to what they are doing. Engineering examples of these key terms are adiabatic, fully developed flow, heterogeneous, and steady state. In my pilot studies, students often identified the steady state assumption given in the problem statement. Many of them even correctly stated that this meant that nothing was changing with time, but none of the students connected this to the overall energy balance to solve the problem correctly. In the Chi study, the experts derived a second-order interpretation (involving features that were not explicitly stated in the problem) from these 1st order features, and then developed general solution plans from these. Novices only noticed the first order features and chose equations based on those features. Experts hypothesized about the physics principle that could be involved. Then they used the 1st and 2nd order features of the problem to choose between potential hypotheses. Novices immediately started talking about the equations involved in a potential solution.

In their classic study of chess masters, Chase & Simon (1973) found that experts do not have superior memory capacity; they are able to remember more information because they chunk related information together. Saariluoma and Kalakoski (1997) found no differences between visual and auditory presentation in blindfolded chess. Differences in performance resulted from differences in knowledge, not imagery ability (Gobet & Charness, 2006). In chess, experts use their visual-spatial working memory more than verbal working memory. Campelli and Gobet (2005) found that chess masters are able to filter out constant irrelevant information. When irrelevant information changes throughout the game, chess masters ability to recall the game sequence is reduced. This has implications in understanding how expert perception affects performance.

Although the bulk of expertise research was conducted using routine problems and situations, more recent research has started to focus on how experts perform in innovative situations. In the next section, I discuss the research conducted on adaptive expertise and expertise in novel situations.

ADAPTIVE EXPERTISE

Hatano & Inagaki (1986)introduced the theoretical concept of adaptive expertise based on definition of routine and adaptive experts (Hatano & Inagaki, 1986). Since then, the construct has been further defined (Schwartz, et al., 2005) and tested by numerous empirical studies (Crawford, Schlager, Toyama, Riel, & Vahey, 2005; Martin, Petrosino, Rivale, & Diller, 2006a; Martin, Pierson, Rivale, & Diller, in press; Martin, Rayne, Kemp, & Diller, 2005; Martin, Rivale, & Diller, in press; Pandy, Petrosino, Austin, & Barr, 2004; Rayne, Martin, Brophy, & Diller, 2006; Rivale, Martin, & Diller, 2006). Most of these studies have focused on learning and learning trajectories and not experts. However, a few studies have investigated experts working on novel problems and rare cases (see Table 2.2) (Alberdi, Sleeman, & Korpi, 2000; Carlson & Bloom, 2005; Feltovich, Spiro, & Coulson, 1997; Schraagen, 1993; Schunn & Anderson, 1999).

Table 2.2: Experts in Novel Situations

Reference	Results/Contribution	Methodology	Expert-Novice Categories	Theoretical Framework	Domain
(Feltovich, Spiro, & Coulson, 1997)	Introduce "reductive bias" and complexity/complex systems explicitly into theories of expertise	Theoretical Review Case study Protocol Analysis	Qualitative expert case	Complex Systems	Medicine
(Alberdi, Sleeman, & Korpi, 2000)	When confronted with a surprising data, experts revert to more abstract domain knowledge to revise hypothesis.	Protocol Analysis Compared to previous model	Expert Taxonomist (n=5)	Concept acquisition Scientific reasoning	Taxonomic Botany
(Hmelo-Silver & Pfeffer, 2004)	In complex systems novices focused on perceptually available structures, where experts focused on behaviors and functions. There was a difference between academic experts and hobbyists in the type of knowledge used: biologists more abstract and hobbyists more contextualized.	Protocol Analysis Structured Interviews	7^{th} graders (n=11) pre-service teachers (n=11) Experts (n=8) academic biologists & aquatic hobbyists	Structure-Behavior-Function Theory	Aquatic systems
(Schraagen, 1993)	When confronted with a novel task experts without sufficient domain knowledge retain their general strategies, but the content suffers from lack of domain knowledge	Task Analysis Categorization Protocol Analysis	undergraduates (n=9), graduate students (n=3), design experts (n=3), and domain experts (n=4).	Problem Solving	Experimental Design (Psychology)

Table 2.2 (cont). Experts in Novel Situations

Reference	Results/Contribution	Methodology	Expert-Novice Categories	Theoretical Framework	Domain
(Schunn & Anderson, 1999)	Experts have both domain specific skills that are dependent on their content knowledge and domain general skills (that transfer across expertise specialties that undergraduates do not have)	Protocol Analysis Evaluation of computer simulation tracking	Undergraduates (n=30) Task experts (n=6) Domain experts (n=4)	Scientific reasoning	Experimental Design (Psychology)
(Carlson & Bloom, 2005)	4 phase cyclic framework: orienting, planning, executing, checking Experimentally validate expert problem solving behavior on novel problem -verify and expand (Schoenfeld, 1985)	Protocol Analysis Grounded Theory	n=12 (8 research mathematicians, 4 adv PhD.)	Problem Solving, Heuristics	Mathematics

Although there have been numerous studies characterizing experts and comparing experts to novices, there has been less longitudinal research to explain how these important aspects of AE develop. (Lajoie, 2003) Schwartz, Bransford, and Sears (2005) have proposed a theoretical model of AE development (See Figure 1). This model assumes that AE development is a continuous process that includes axes for growth along two dimensions: (a) innovation and (b) efficiency. Schwartz, Bransford, and Sears (2005) have hypothesized that these two dimensions co-evolve in what they have called the "optimal adaptability corridor" (OAC). The OAC hypothesis is that instruction that develops innovation and efficiency together will lead students to progress further along a trajectory toward AE than instruction that teaches for either efficiency or innovation first.

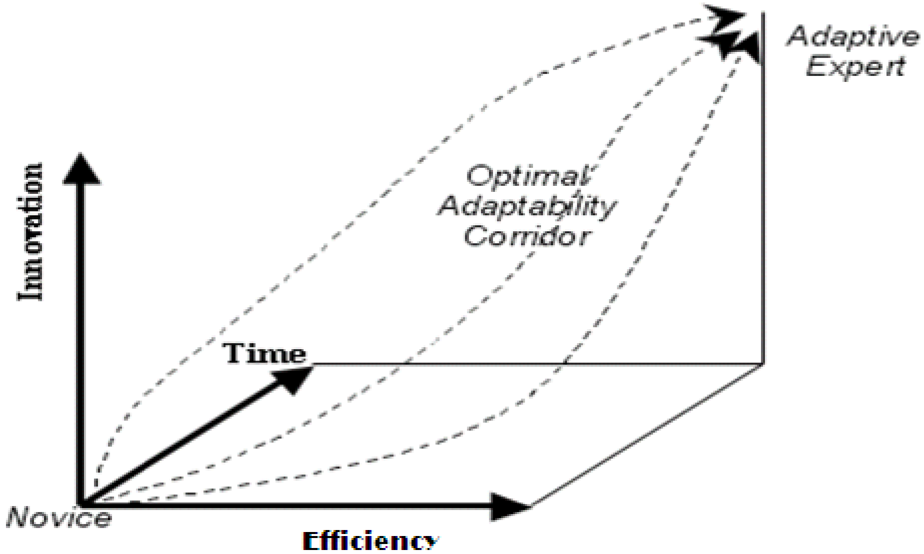


Figure 2.1: Developmental Model for Adaptive Expertise.

Classic studies tended to study two groups, experts and novice. More recent studies have also had a more developmental approach, including both intermediates and different kinds or groups of experts (Hmelo-Silver & Pfeffer, 2004; Raufaste, et al., 1998; Schraagen, 1993; Schunn & Anderson, 1999; Wineburg, 1997). Study designs have included both task-experts and domain experts (Hmelo-Silver & Pfeffer, 2004; Raufaste, et al., 1998; Schraagen, 1993; Schunn & Anderson, 1999; Wineburg, 1997). This experimental design has helped to differentiate how experts use domain specific knowledge and general scientific reasoning skills and heuristics. Two studies investigated expertise in experimental design. This eliminated the need for knowledge elicitation of experts in defining the domain tasks since they were able to use expertise within the cognitive science domain.

In the Schraagen (1993) study, participants were asked to design a cola taste test. The study contrasted performance of beginners (undergraduate students), intermediates (graduate students), task experts (psychology professors with experience in experimental design), and domain experts (gustatory researchers.) Task experts and domain experts were matched on everything but specific knowledge about taste and other experimental results in the field. The experts came up with more designs and spent more time on task. Although design experts scored higher than the novices, this difference was not significant. The design and domain expert scores were significantly different. Design experts used a more controlled general strategy but their lack of domain knowledge affected the quality of their solutions. The authors found when experts are confronted with novel problems, as compared with familiar problems, their form of reasoning remains intact, but the content of their reasoning suffers due to lack of domain knowledge. Design experts and intermediates used mental simulation strategies but the domain experts and the beginners did not. However, this should not be interpreted as beginners being more expert-like; the domain experts more than likely did not need to use this process because their domain knowledge and experience allowed them “to know” the answer.

Schunn and Anderson (1999) used a computer model, Simulated Psychology Lab, which allowed the participants to see the results of the experiments that they designed. Subject were asked to design and interpret experiments to test two theories that explain memory spacing effect so the domain experts were cognitive psychologists who specialized in memory and the task experts were developmental to social psychologists. They found that the domain specialists outperformed the task experts, but that there were many design process skills that were similar in both groups. They also compared the experts to both high ability and average undergraduate students; the design process skills were lacking in both student groups.

Carlson and Bloom (2005) studied 12 mathematics experts solving problems. Each of the experts solved four novel problems that were challenging, required math content accessible to all mathematicians (were not specialty restricted), a variety of solution paths were possible, and were complex enough to lead to dead ends to study affective components. Originally, the verbal solutions were coded using a framework constructed from previous work in problem solving. This was not comprehensive so the authors used grounded theory methods to create a "Multidimensional Problem-Solving Framework". The cyclic framework included 4 phases: orienting, planning, executing, and checking. Initially, the experts oriented themselves with the problem, similar to representation or problem definition. Then, in the last three iterative phases, the experts would plan, execute and check again.

Alberdi et al. (2000) investigated categorization strategies used by expert botany taxonomists. The study used the Korpi (1988) model of categorization. Korpi's study relied on common sense knowledge, whereas this study explicitly tested subjects with significant domain knowledge. This study tested how scientists use their domain knowledge in categorization. The study was also designed to test how scientists respond to surprising information or data. Subjects were presented with an illustration of a plant what initialed seemed to fit a particular classification. However, the plant illustration would have one inconsistent characteristic that would invalidate the initial categorization hypothesis. This design strategy was used to mimic how scientists consider analogous data. The study found that experts often revert back to their domain knowledge to generate new hypotheses when they encounter inconsistent data or information.

As a collection, these studies (Alberdi, et al., 2000; Carlson & Bloom, 2005; Schraagen, 1993; Schunn & Anderson, 1999; Wineburg, 1997) revealed some important characteristics of expertise. They have all looked at experts in novel situations. They represent various domains: botany, mathematics, experimental design, and history. Together they test differences in two general types of expert, domain experts/specialists and task experts. The Lincoln specialists (Wineburg, 1997), gustatory experts (Schraagen, 1993), memory experts (Schunn & Anderson, 1999), mathematicians (Carlson & Bloom, 2005) and botany taxonomists (Alberdi, et al., 2000) are all domain experts, and the American history specialists (Wineburg, 1997) and experimental design experts (Schraagen, 1993; Schunn & Anderson, 1999) are task experts. As a collection, they speak to the interaction of declarative (know what) and procedural (know how) knowledge in experts. That domain experts utilize their background knowledge in novel situations is not a surprising result. These studies also show that task-experts are able to transfer procedural knowledge, general approaches and heuristics to novel situations. These studies showed fairly consistent results across fairly different types of tasks, namely, design, categorization and problem solving, with a few minor differences. In both experimental design studies, the overall design quality of the task experts was more similar to novices than the domain experts, but their general approach (heuristics) was similar to the domain experts. In the Wineburg (1997) study, the American history specialists started at a level similar to pre-service teachers but were able to use their procedural knowledge to end up at the same place that the Lincoln experts started. These results are not inconsistent. The task constraints differed across studies. In the experimental design studies, the participants were not given outside resources or opportunities to learn or find the missing background knowledge, whereas, the nature of the Wineburg study allowed the American history specialists to gain more knowledge from the actual documents that they were analyzing in the experiment.

These studies can guide our understanding of expertise in engineering. There are many similarities to problem solving in mathematics and physics, especially at the introductory level. Although the problems in Carlson study were not textbook-like problems, they were constrained problems with an analytical solution. Some of the problems were actually simple once you figured out the trick to solving them. For example in the ladder problem, the solution become simple if the solver realized the there is a proportional relationship between the height of the ladder and the distance to the wall that can be treated as a first order derivative. However, it is important to note the differences between the domains. In general, the goal of most scientific studies is to understand and explain natural phenomenon and add to our collective knowledge base. Whereas in engineering, the goal is to add to the state of the art and create things that have never existed before. So while novel solutions are desirable in most fields, it is essential in engineering, especially engineering design. Engineers do many things, but most often they are designers who optimize under constraints. Therefore, although it can be argued that innovation is a desirable skill/quality in any domain, innovation drives engineering design.

There have been numerous studies using the construct of adaptive expertise (see Table 2.) Schwartz, Bransford and Sears (2005) proposed that adaptive expertise is comprised of two dimensions: efficiency and innovation. They defined efficiency as the ability to "rapidly retrieve and accurately apply appropriate knowledge and skills to solve a problem or understand and explanation". Practice and experience are good ways to promote efficiency. A big part of efficiency is problem elimination rather than deep problem solving. Efficiency can be seen as near transfer, putting the present state very near the goal state. Innovation had a less precise definition. Innovation is often preceded by a sense of disequilibrium, often requires a movement away from what is momentarily most efficient. Sometimes there is a need to resist initial ideas that initially seem most efficient. Reframing the problem is also important, as discoveries are often the result of looking at something from a new perspective. Schwartz et al. (2005) give the example of experts trying to design a picking machine that would not bruise tomatoes. However, the innovative solution was to produce a new strain of tomatoes that are less easily bruised.

Table 2.3: Adaptive Expertise Studies

Reference	Results/Contribution	Methodology	Expert-Novice Categories	Theoretical Framework	Domain
(Hatano & Inagaki, 1986)	Two different types of expertise: routine and adaptive Introduction of adaptive expertise	Theoretical	Theoretical	Adaptive expertise	Sushi experts
(Raufaste, Eyrolle, & Marine, 1998)	Contrasted experts and super-experts (teaching and research experience) Observed U-curve (more knowledge less flexibility in intermediates)	Protocol Analysis Dictation	novices (n=8), intermediates (n=8), basic experts (n=4) and super experts (n=4).	Perception	Medicine (Radiology)
(Schwartz, Bransford, & Sears, 2005)	Introduced innovation and efficiency dimensions of adaptive expertise	Theoretical	Theoretical	Adaptive expertise	Learning sciences
(Pandy, Petrosino, Austin, & Barr, 2004)	Differentiated adaptive expertise into factual, conceptual and transfer components	Problem solving Pre/Post-test	Undergraduates (n=25)	Adaptive expertise, HPL	Biomedical Engineering (Biomechanics)
(Crawford, Schlager, Toyama, Riel, & Vahey, 2005)	Definition of "adaptive" teacher behavior: slow to draw conclusions, build models (mental) from evidence, systematic exploration of data, attentiveness in drawing conclusions, build understanding through data, high interest and curiosity, anticipate novel content, disposition to learn novel information	Protocol Analysis	High school biology teachers (n=11)	Adaptive expertise	Teaching

Table 2.3 (cont). Adaptive Expertise Studies

Reference	Results/Contribution	Methodology	Expert-Novice Categories	Theoretical Framework	Domain
(Martin, Rivale, & Diller, in press)	HPL methods promotes more expert-like and adaptive performance than traditional teaching methods More specifically students were able to learn and apply expert problem solving methods when type of learning was integrated with knowledge instruction	Problem solving Pre/Post-test	Undergraduates (n=106; HPL=54 & trad=52)	Adaptive expertise, HPL	Biomedical Engineering (Biotransport)
(Martin, Pierson, Rivale, & Diller, in press)	Generate Ideas helped students develop multiple perspectives and metacognition, Engaging in an open Generate Ideas followed by a more directed Generate Ideas activity promoted adaptive expertise better than directed alone	Problem solving Self-report surveys Pre/Post-test	Undergraduates	Adaptive expertise, HPL	Biomedical Engineering (Biotransport and Ethics)
(Rayne, Martin, Brophy, & Diller, 2006)	Undergraduate students less flexible (U-curve observed by (Lesgold et al., 1988) and (Raufaste et al., 1998))	Pre/Post-test	High school students (n=11) Undergraduates (n=102)	Adaptive expertise, HPL	Biomedical Engineering (Ethics)
(Martin, Rayne, Kemp, & Diller, 2005)	HPL and traditional instruction result in similar learning of factual information HPL prepared students to be more adaptive in a novel situation	Pre/Post-test	Undergraduates (n=35)	Adaptive expertise, HPL	Biomedical Engineering (Ethics)
(Rivale, Martin, & Diller, 2006)	There were gender differences in performance, but not in beliefs. Females had lower initial performance, but showed more improvement at end they performed similarly on all measures	Problem solving Self-report surveys	Undergraduates (n=54)	Adaptive expertise, HPL	Biomedical Engineering (Biotransport)

Crawford et al. (2005) attempted to define adaptive expertise within the context of high school biology teaching and to relate discerning student understanding to problem solving. The study was designed to contrast both novice and experienced teachers, but in this report only experienced teachers' performance (n=9) had been analyzed. In a two-hour laboratory session, teachers were asked to analyze student work and diagnose student understanding. The researchers used think aloud protocol and cognitive task analysis to discern teacher thinking. The teachers were given the scenario that they were taking over a 10th grade biology class of 22 students that just completed a genetics unit. The teachers were given scored end-of-the-unit practice tests, consisting of multiple choice and open-ended questions, a test key, a spreadsheet summary of individual students' performance on each test question, a grade book, lesson plans, and a textbook. The student test results were designed with common misconceptions embedded in them. In addition, novel content (non-ribosomal peptide synthesis) was embedded as part of the test questions to test adaptive-ness, curiosity and disposition for lifelong learning. The primary contribution of this study was the definition of "adaptive" teacher behavior. "Adaptive" teachers are slow to draw conclusions and do so attentively. They build mental models from evidence and understanding through systematically explored data. With a disposition to learn novel information, they anticipate novel content with high interest and curiosity. The primary limitation of this study results from the preliminary nature of the report, they only analyzed experienced teachers. Since the novice teachers were not observed or analyzed for this report, a comparison between novice and experienced teachers cannot be made. Future results comparing these two groups will be interesting.

The Vanderbilt Northwestern Texas Harvard-MIT Engineering Research Center (VaNTH) project has produced numerous studies of the development of adaptive expertise in biomedical engineering undergraduates (Martin, Petrosino, Rivale, & Diller, 2007; Martin, Pierson, et al., in press; Martin, et al., 2005; Martin, Rivale, et al., in press; Pandy, et al., 2004; Rayne, et al., 2006; Rivale, et al., 2006; Roselli & Brophy, 2006). Pandy et al. (2004) explained adaptive expertise in biomechanics as a linear combination of factual, conceptual knowledge and transfer. In a biotransport class using HPL methods, students' abilities to solve novel problems improved throughout the semester (Martin, Petrosino, et al., 2007). Large gains were linked to modeling and teaching an expert-like problem solving approach (Martin, Petrosino, et al., 2007; Martin, Pierson, et al., in press). This problem solving approach is the engineering equivalent to the general approach that task-experts used in the experimental design studies (Schraagen, 1993; Schunn & Anderson, 1999). In a direct comparison, students taught using HPL methods approached open-ended novel biotransport problems more adaptively and expert-like than students taught using traditional lecture methods (Martin, Rivale, & Diller, 2007). Roselli and Brophy (2006) reported similar results in biomechanics. Rayne et al. (2006) implemented an ethics module about stem cells in both high school and university classrooms. They found that undergraduate students, who had more knowledge about the subject at the pre-test, were less adaptive on the posttest problem. This might be consistent with the U-curve results observed by Lesgold et al. (1988) and Raufaste et al.

(1998). Undergraduates are normally thought of as novices, not intermediates, in expert research. However, since, less background knowledge is necessary to solve the ethics module than in other engineering and physics domains, they could arguably be considered intermediates in this experiment. Overall, these studies show promising results that HPL methods improve student performance on novel tasks. If this is simply a result of more deliberate practice (Ericsson, 2006a) or is actually speeding up the development of expertise remains to be seen. The 10-year rule has been shown to be fairly robust across domains (Ericsson, 2006a).

Several researchers have investigated differences in the understanding and use of complex systems in experts and novices (Hmelo-Silver & Azevedo, 2006; Hmelo-Silver & Pfeffer, 2004; Hmelo, Holton, & Kolodner, 2000; Jacobson & Wilensky, 2006) and student misconceptions (Chi, 2005; Hmelo-Silver & Azevedo, April 2006; Resnick & Wilensky, 1998; Wilensky & Reisman, 2006; Wilensky & Resnick, 1999). In general these studies have found that experts are more likely to explain complex systems in terms of interactions and emerging phenomena, where novices and naïve adults tend to oversimplify systems into direct causal events.

Hemlo-Silver and Pfeffer (2004) conducted an expert-novice study using an aquarium as a complex system. There were two groups of novices, suburban 7th graders and pre-service teachers, and two types of experts, academic biologists and aquarium hobbyists with at least 10 years of experience. They used a think aloud method as each subject drew an aquatic system. Then after the drawing task was complete, they used a structural interview to elicit further understanding of subjects' knowledge of aquatic systems. They analyzed the results using Structure-Behavior-Function (SBF) Theory: structures are individual components, behaviors are the mechanisms, and functions are the more abstract processes. Expert protocols differed from novices' in the number of behaviors and functions they contained. There were no differences between 7th graders and pre-service teachers. At a qualitative level there were differences between the biologists' and the hobbyists' responses. Biologists' knowledge was more abstracted and hobbyists' knowledge was more situated.

Alberdi et al. (2000) found that when expert taxonomists encountered surprising plant features that were not consistent with their categorization schema, they proceeded to think about plant features more abstractly. If you assume that their knowledge is organized hierarchically, they accessed the category more broadly. For example they tried to classify the plants general fruit or flower type of the group of items. Hmelo-Silver and Pfeffer (2004) also noticed differences in the type of knowledge and reasoning of aquatic biologists and hobbyist. Biologists' knowledge was more abstract (mention basic functions and behaviors), and hobbyists' knowledge was more situated. Feltovich et al. (1997) also discuss abstraction, "there have been demonstrations that experts retain a capacity to override schema-driven processing, to engage in a deeper, more basic kind of reasoning from first principles when they need to, particularly in difficult cases." They also argue that novices comprehend complex systems by over-simplifying them, calling this "reductive bias." Zietz (2006) has proposed that abstract representation "may be a necessary precursor to integration of information and perception of coherent patterns."

Political science experts also gave more abstract representation of problems than novices (Voss, Tyler, & Yengo, 1983).

In summary, level of expertise affects knowledge organization and abstraction. Other researchers have found performance differences based on level of specialization in the task and field. Since these results are consistent across numerous domains, I expect similar results in engineering experts. This study will contribute to more refined answer in engineering. Are there common heuristics that are followed by most engineering experts? Where does knowledge specialization impact performance?

METHODOLOGIES USED IN THE STUDY OF EXPERTISE

Traditionally, four different methods have been used to examine expertise and expert-novice differences: categorization, perception, recall, and verbal reporting (Chi, 2006). Categorization methods have been used to examine how an expert's knowledge is organized. Perception methods are primarily in domains like medicine and chess where visual perception is a more required skill. Recall methods are most commonly used to test and understand the role of memory in expertise. Verbal reporting methods have been used to understand problem solving behaviors.

Most studies have used two different types of verbal reporting methods: concurrent and retrospective reporting. The validity and reliability of these two verbal reporting methodologies have sparked considerable controversy. Some studies have shown that verbal reporting improves performance on problem solving tasks (Gagne & Smith, 1962) and that retrospective explanations are often inconsistent with observations

(Nisbett & Wilson, 1977). Ericsson and Simon (1980, 1984, and 1993) found that validity depends on the amount of time between the occurrence of a thought and verbal report of the thought. Experimental results showed that intervals between 5-10 seconds and 10-30 seconds are valid. However, intervals longer than 30 seconds increase the likelihood of differences between the actual thought and what is verbally reported by the subject (Ericsson, 2006b).

Ericsson and Simon have reviewed both the validity and reliability of concurrent and retrospective reporting methodologies (Ericsson, 2006b; Ericsson & Simon, 1984, 1993). They classify verbal reporting methods into three categories. Type 1 (talk aloud), Type 2 (think aloud), and Type 3 (explanation). Talk aloud and think aloud verbalizations are concurrent methods; the subjects are asked to verbalize their thoughts as they are performing the cognitive task. The difference between the two types depends on whether or not the information being processed in the task is already in verbal form. In the talk aloud method (Type 1), information is already in verbal form. An example of this would be recalling numbers or letters to an interviewer. The think aloud method (Type 2) requires an additional process, as subjects need to encode each thought into verbal form before they can actually verbalize it. Most problem solving studies have used the think aloud method since they require verbal encoding. In both of these concurrent methods, each individual thought is verbalized before progressing to the next thought. Type 3 (explanation) is a retrospective process where subjects are asked for explanations or reasons for their behavior. Subjects cognitively process a string of thoughts, then encode and verbalize them. They typically report back to the interviewer after the task, or subset of the task is completed. This study uses both Type 2 and Type 3 methods. Experts were instructed to think aloud as they are solving the problem. Then after they completed the problem, they gave a retrospective explanation of the process they used to solve the problem.

DIFFERENCE IN SPECIALIZATION

Some previous studies have used two different types of experts: domain experts and task experts (Schraagen, 1993; Schunn & Anderson, 1999; Wineburg, 1997). This study design capitalizes on the specialized knowledge differences between domain experts and task experts while limiting the differences in the amount of practice time inherent in expert-novice studies. Using think aloud protocol methodology, Wineburg (1997) studied two history experts' interpretations of primary history documents about Abraham Lincoln and his view of race. Both historians were American history professors of equal recognition. However, the first historian specialized in the Civil War era and was very familiar with Lincoln and the era, and the second historian had domain knowledge which was not as specialized as Civil War expert's knowledge. In the Schraagen (1993) study, experts were asked to design a taste test. She used two types of experts: design experts (experimental psychology experts) and domain experts (gustatory specialists). The design experts were experimental psychology experts with design expertise but they lacked the gustatory expertise relevant for the design task they were given. I used a similar study design. Three of the experts have expertise in heat transfer (domain experts). The task experts in this study are engineers with less heat transfer research and teaching experience.

PROBLEM SOLVING

Problem solving has been extensively studied (refs). In this section I will discuss the highlights of this literature and the studies that directly influence this study. In mathematics problem solving, Polya (1945) broke the problem solving process down into four general phases: (1) understand the problem, (2) devise a plan, (3) carry-out the plan, and (4) examine the solution. Schoenfeld (1985) built on Polya's by expanding the problem solving steps into an alternative framework that consists of four categories: (1) resources, (2) heuristics, (3) control, and (4) belief systems. He defines resources as the mathematical knowledge that the problems solver brings to the process. Examples of resources are facts, algorithms, intuition and informal knowledge. Heuristics are the general "strategies and techniques for making progress on unfamiliar or nonstandard problems; rules of thumb for effective problem solving." Some common heuristics are drawing figures, working backwards, and exploiting related problems. He defines control as the "global decisions regarding the selection and implementation of resources and strategies" like planning, monitoring, assessment and other metacognitive acts. An individual's beliefs about her or himself, the environment, the topic and mathematics itself make a person's belief system or "mathematical world view."

Carlson and Bloom's (2005) conducted an expert study of mathematical problem solving. Originally, the verbal solutions in this expert study were coded using a framework constructed from Shoenfeld's (1985) problem solving framework. However, the authors found that, "t his framework did not fully explain the reasoning patterns and interactions that they were observing. In particular, they noticed that their framework was limited in its ability to characterize specific interactions between the problem-solving process and aspects of the subjects' cognitive processes, metacognitive behaviors, and affective responses (Carlson & Bloom, 2005)." So they completed a second analysis using grounded theory methods to create a "Multidimensional Problem-Solving Framework." That included 4 phases: orienting, planning, executing, and checking.

In previous studies of the development of adaptive expertise in biomedical engineering studies, our research group coded student solutions to open-ended novel problems similar to the one used in this study using a rubric of 5 categories. This rubric was based on the instructor's, an expert in the field, own problem solving method. First, this method encouraged students to define the system. After determining what aspects of the problem were included in the system, the next step is to identify how this system interacts with the surrounding environment. Then, students should think about what governing principles, such as the conservation of energy, apply to the problem and identify the correct constitutive equations, such as the rate equations for conduction or convection. In the final step students solve the problem (Martin, Pierson, et al., in press; Martin, Rivale, et al., 2007). The rubrics in these studies were based on the problem solving process of one expert. This study can shed light on the whether this process is common of most engineering experts or if there are significant variation among engineering experts.

This study is informed by the expertise and problem solving literature. The following chapter explains the methods used in this expert study. The participants, problems and procedures used in this study will be explained. Then the coding and analysis is explained in more detail

Chapter 3: Methodology

According to the *Engineer of 2020*, future engineers need to be innovative problems solvers; creative, flexible, resilient with a passion for lifelong learning(Clough, 2004). To further clarify what this looks like in an educational context, this study examined experts' performance on both routine and non-routine heat transfer problems. Categorization, perception, recall, and verbal reporting, the four traditional methods used to examine expertise and expert-novice differences, were discussed in more depth in the previous chapter. This study used a combination of concurrent and retrospective verbal reporting methods because they are more conducive to understanding problem solving behaviors. The controversy about the validity and reliability of verbal reporting methodologies was also discussed in more length in the previous review of the literature. Since validity is increased when the subject verbalizes each thought within 30 of the occurrence of the thought, I used the think aloud protocol methodology developed by Ericsson and Simon (1984).

In this chapter, I first describe the experts that participated in the study. Then, I explain the two problems and how they were selected. In the procedure section, I present a chronological description of how the study was executed. I then discuss the coding and analysis of the transcripts.

PARTICIPANTS

Seven engineering experts participated in the study (5 men and 2 women). They averaged over 28 years of teaching and research experience. I initially used a relative perspective to classify university professors who teach or conduct research in engineering as experts. With the assistance of the domain expert on my committee, I identified and solicited heat transfer experts from two Research I universities. Originally, I tried to solicit half the expert pool as domain experts with specialized knowledge of heat transfer in porous media and the other half heat transfer experts less familiar with heat transfer in porous media. However, only one of the experts had significant experience porous media heat transfer. He had conducted research in this area for many years. Another expert had worked on these types a problem in a job in industry many years ago, but no longer considered herself an expert in the area; a third expert said he was familiar with porous media problems. The rest of the experts had no experience solving or conducting research in porous media heat transfer. Among the experts that volunteered for this study two different expert groups emerged. One group had both heat transfer and general engineering expertise. The second group, had been exposed to heat transfer principles in both their graduate and undergraduate education, but they never taught transport or conducted research in the area (See Figure 3.1 and Figure 3.2).

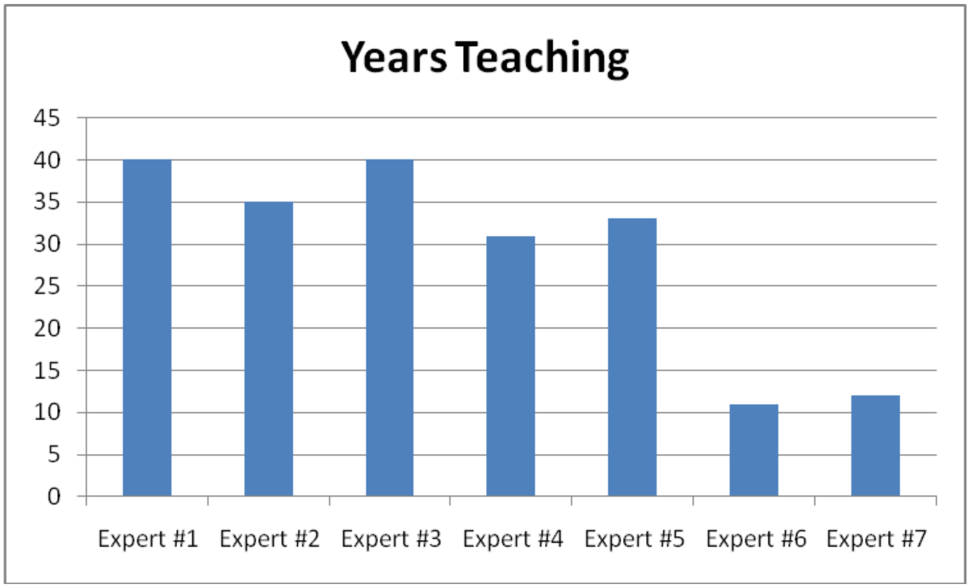


Figure 3.1: Engineering Teaching Experience

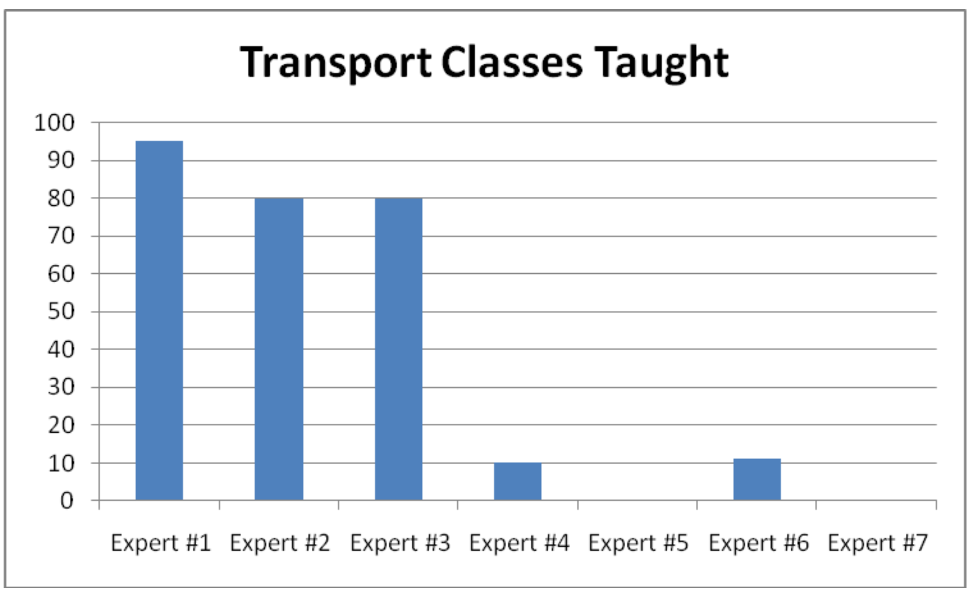


Figure 3.2: Transport Teaching Experience

This study design parallels previous work done in history (Wineburg, 1997) and experimental design (Schraagen, 1993; Schunn & Anderson, 1999) that used two different types of experts: domain experts and task experts. These two studies were described in more detail in the previous chapter. However, the experts' experiences in this study are not as clearly delineated into domain experts and task expert categories. Five of the seven experts in this study had over 30 years of engineering teaching experience, and the additional two experts both had over 10 years experience. Expert 7 is the only non-tenure track professor. She worked in industry in for over 10 years as well on projects with significant heat transfer components. In terms of specific transport teaching experience, the experts fell into three categories of experience: having taught over 80 different transport courses (3), having taught over 10 transport courses (3), and never having taught a transport course (1). This expert actually had not taken a heat transfer course since his he was an undergraduate over 30 years ago. Five of the seven experts have conducted research in heat transfer. Although one of these was only in PhD work and one was in industry as significantly smaller portion of the expert's job responsibilities. Only one of the experts had very much experience solving or researching porous media problems. This is important because this is one of the ideal solution paths for the complex problem. It is also worth noting that Expert 6's research specialty is biomaterials and cell biology. This is significant because the bee's metabolism and physiology add complexity to the ill-structured problem. In comparison to the prior expert-expert study designs, Expert 1, Expert 2 and Expert 3 could be classified as task experts and Expert 5 could consistently be classified as a domain expert. The remaining experts would fall somewhere in the middle. Although considering the 10 year rule there might not be much difference between the high and medium levels teaching and researching in the heat transfer domain. Since this study was initially proposed as a novice-expert study, it was designed under Chi's (2006) relative approach. Since we had limited access to the experts in this study, no additional knowledge assessments were given. However, since the routine problem covers the same taxonomy as the complex problem. The routine problem will be used as heat transfer expertise validation. Tables 3.1 and 3.2 summarize the different relevant teaching and experiences of the experts in this study. Although not ideal, the varying specialization differences lend themselves to the study of adaptive expertise.

Table 3.1: Expert Experience

	Task Experts			Domain Expert
	Expert #3	Expert #1	Expert #2	Expert #5
Engineering Teaching	High > 30 years	High > 30 years	High > 30 years	High > 30 years
Transport Classes	High > 80	High > 80	High > 80	None
Heat Transfer Research	Yes	Yes	Yes	None
Porous Media	High	None	None	None
Physiology	None	None	None	None

Table 3.2: Expert Experience

	Mixed Experience Mixed Specialization		
	Expert #4	Expert #6	Expert #7
Engineering Teaching	High > 30 years	Medium 10-15 years	Medium 10-15 years
Transport Classes	Medium 10-15 classes	Medium 10-15 classes	Medium 10-15 classes
Heat Transfer Research	Some	None	Some
Porous Media	Some	None	Some
Physiology	None	High	None

MATERIALS

PROBLEMS

Study participants were asked to solve two problems – a non-routine complex problem and a routine textbook-like problem. The non-routine problem was chosen to access innovation and efficiency. To aide in the comparison to previous expertise research, the second problem is a general textbook-like problem. This is a problem a student completing a transport or heat transfer class would be expected to be able to solve. The non-routine problem needed to be novel and complex enough to push the limits of the experts' knowledge. Using these criteria, I surveyed the test bank for VaNTH biotransport course. On every exam, students were given an open-ended far transfer problem that tested their ability to apply the knowledge they were learning in the course in a complex novel problem situation. From this test bank of problems, I selected three potential problems and discussed them with our research team multiple times. I then piloted these three problems with a colleague who completed a PhD in chemical engineering and teaches the introductory material and energy balances course at her institution.

From the pilot study, I selected the Bee Hive Problem for this study (See Appendix A). This problem piloted well. It was complex enough to push the pilot expert's knowledge. The two other problems that I piloted were too easy from an engineering perspective and were not as assessable to engineering experts because they lack necessary biological knowledge critical to the problem solution. The selected non-routine *Bee Hive Problem* is based on a 2004 *Science* article about genetic diversity and temperature regulation in bee colonies (Jones, Myercough, Graham, & Oldroyd, 2004). This problem asks participants how they would quantify transient hive temperature to determine whether genetic diversity helps stabilize hive temperature by analyzing and modeling the process.

Once non-routine problem was chosen, I selected a routine problem that required a similar knowledge base to solve but was simpler and more straightforward. The problem is a simple steady state energy balance problem (see Appendix A) taken out of a standard introductory heat transfer textbook (Incropera & DeWitt, 2002) The problem asks participants to solve for the inside temperature of a brick wall given all the necessary variables.

Table 3.3 compares the knowledge base required for both problems. Both problems are solved using Conservation of Energy; the solutions require participants to conduct an energy balance. In addition, both problems involve all three modes of heat transfer: conduction, convection and radiation. However, the routine problem is simpler than the non-routine problem because it assumes that the system is at steady state, reducing a differential equation to a simple algebraic manipulation. The routine problem is also a one dimensional problem, whereas the non-routine problem involves a complex three dimensional geometry. And finally, all of the thermal properties necessary to solve the problem are given in the routine problem. In the non-routine problem, the thermal properties are complex, requiring additional assumptions or a plan to obtain them experimentally.

Table 3.3: Transport Taxonomy Comparison

Problem	Routine - Brick	Non-routine - Bee Hive
Problem Constraints	Highly prescribed	Open-ended
Governing Principle	Conservation of Energy	Conservation of Energy
Modes of Heat Transfer	Conduction Convection Radiation	Conduction Convection Radiation
Conditions/Assumptions	Steady State	Transient
Geometry	1 D	Complex 3 D
Thermal Properties	Given	Complex, not given

PROCEDURE

This study was conducted with IRB approval. Participants were solicited without compensation to volunteer to solve two heat transfer problems and interviews set up by email. At the beginning of the interview, they were asked to read and sign a consent form and to fill out brief demographic information.

At the beginning of the interview, I briefly explained the purpose of the experiment and the think aloud process (see Appendix B for the interview protocol). Then I modeled the think aloud process using a simple addition problem. I gave them a different simple addition problem to solve while thinking aloud as a warm-up exercise. At the end of the warm-up exercise, students are asked to explain what they remember thinking about the problem (to summarize their problem-solving process). After the warm-up, I gave participants the first non-routine Bee Hive Problem. While they were solving the problems, I did not interact with the participants except to remind them to keep talking out loud. After they have completed their solution, I asked them to give a retrospective report of their process – what they remembered thinking in sequential order as they were solving the problem. This process was then repeated for the non-routine problem. Participants solve the problem aloud and then report back on their process.

After solving the two problems, participants were asked a couple of quick questions about their teaching and research experiences in the transport domain. All participants were also asked what systems they thought could be solved analogously to the Bee Hive problem. This question was designed to uncover whether they have thought about the problem based on deep principles or more on surface features as Chi et al. (1984) have found. They were also asked about their experiences with heat transfer in porous media since that is the taxonomic knowledge base associated with the solution to the Bee Hive Problem. In an attempted to refine the definitions of innovation and efficiency in an educational context; participants were asked what their personal definition of innovation and efficiency are.

These audio taped interviews were then transcribed. The transcriptions were coded using *Altas ti* software. They were coded in multiple rounds. In the first round, a grounded theory open coding technique was used. In subsequent rounds, protocol analysis methods were used (Ericsson & Simon, Chi). Chi (1997) recommends that the analysis should be broken down into the following eight steps:

1. Reducing or sampling the protocols.

2. Segmenting the reduced or sampled protocols (sometimes optional).
3. Developing or choosing a coding scheme or formalism.
4. Operationalizing evidence in the coded protocols that constitutes a mapping to some chosen formalism.
5. Depicting the mapped formalism (optional).
6. Seeking pattern(s) in the mapped formalism.
7. Interpreting the pattern(s).
8. Repeating the whole process, perhaps coding at a different grain size (optional).

Since this study only used seven experts and two problems, there was no need to reduce the data corpus. As a triangulated approach, the transcribed protocols, field notes, and written solutions were all used in the coding process. The following section explains the coding process used in this study in more detail.

CODING

First Round Coding – Grounded Theory

Initially, the entire corpus was reviewed and coded using an open coding technique consistent with grounded theory. (Strauss & Corbin, 1998) This was done to stay open-minded and reduce bias as much as possible. Although I am familiar with the literature in this area, I did not match the coding to any specific framework during this round. Several themes emerged, but none of them directly answered research questions posed in this study. A couple of unexpected themes emerged related to the professors' beliefs about student development and what types of problems are appropriate for undergraduate and graduate students. They also commented on student performance on these types of problems without being prompted. There were distinct differences in the way the experts approached the challenging problem. Some welcomed it, while others were focused on why it was not a good problem. They were not commenting on flaws in the problem statement, but associating too high of difficulty with a poor problem. Nearly all the experts classified the problem or matched it to analogous problems within the domain. The different backgrounds and experiences of the group impacted solution and the approach they took to the novel complex problem. As a whole, this group verified the expert process used in the Biotransport course and prior innovation coding. The biggest differences in progress to a final solution occurred in the moving from a global energy balance to more detailed analysis, moving between steps 3 and 4 (governing principles to constitutive equations) in this expert process.

Additional Coding – Protocol Analysis

Since the goal of this study is to compare the process that experts use on two different types of problems, the protocols were first segmented by problem type and recall method. The experts both talked aloud while they were solving the problem (concurrent) and then they were asked to recall the process that they use (retrospective). The validity differences in these two methods were discussed in more detail in the previous chapter. Once these portions of the protocol were segmented at this level, each segment was summarized into general process steps (see Table 3.4 as an example). The transcripts were not officially segmented at this finer grain at this point in the coding process. The retrospective portions of the protocols were summarized first in an attempt to reduce the need for interpretation, coding what they said they were doing opposed to what I interpreted them doing from their discourse and written artifacts. However, since it has been shown that delayed recall decreases reliability, the retrospective protocol segments were then compared to the concurrent protocol segments, the field notes, and the written solutions to increase consistency. Table 3.4 is an example of the results of the initial summarization from the retrospective and concurrent segments for one expert.

Table 3.4: Summary Generated from Expert #3

Concurrent Protocol	Retrospective Protocol
Read problem	How much air does flapping put in and out
Comment interesting	Treat as a standard fluids problem
Reading - doing something with givens	Heat balance
Similar to air conditioner	Mass balance
Anticipate question	Mentions "of system"
First try control volume	Classify – porous media heat transfer
General global balance	Prompts important flow distribution?
Implicit – define system	Homogenous?
Implicit – governing principles	Control volume approach
Needs properties	But this problem goes higher
Question if uniform	
Does fanning action propagate to center?	
Or just at surface?	
Is fanning action relevant or neglible?	
What is the distribution? Is it homogenous?	

The collection of segment summaries from all the experts was then reviewed to generate an initial coding scheme (see Table 3.5). As experts read through the problem, they picked out the relevant information from the problem statement. These actions were coded as *Identify Givens*. The *Identify Givens* category included the identification of variables like the initial and ambient temperature, coefficients like emissivity and given constants like the Stephen-Boltzmann constant. These givens were identified in numerous ways: underlining, identifying them verbally, writing them in a list and labeling a diagram with the necessary parameters. Identifying assumptions like whether or not the heat transfer was static or dynamic was also included in the givens. Identifying the question they were trying to answer was coded as *Identify Goals*. Vocalizing that their solution method was determined by the amount of time they had to solve the problem was coded as *identify constraints*.

After identifying the givens, goals and constraints, the experts typically categorized the problem and planned a general approach. These actions were coded as actions guided by *prior experience*. Generally, the initial approach was stated as a global energy balance or control volume approach. However, a couple of experts approached the problem as more of a scientific experiment. Explicitly matching the problem to an analogous problem was also coded in this category. When they categorized the problem, they often reiterated the relevant givens for problem, for example, “this is a one dimensional steady state combined heat transfer problem”. If this action occurred as they were reading the problem it was coded as identifying the givens, but when happened later in the process and as a string of observations it was coded as categorizing the problem.

Table 3.5: Initial Codes Generated from Segmented Summaries

Code	Code ID
Identify Givens	IdGiv
Identify Goals	IdGoal
Identify Constraints	IdCon
Action guided by prior experience/knowledge	Prior
Apply conservation principle	Conservation
Identify modes of heat transfer	XferMode
Bee physiology (temperature regulation)	Physiology
Anticipate question	Anticipate
Type of solution method suggested	Solution
Relate to students	Students
Welcome Challenges	Challenge
Difficulty encountered	Difficulty

The original protocols were then coded using the codes defined in Table 3.6. This initial list of codes was expanded to include more explicit definitions within each of the codes. At this point in the coding process, I attempted to collapse the codes into more general steps. I was able to collapse all of the generated codes into the four phases of Carlson and Bloom's (2005) Multidimensional Problem-Solving Framework: orienting, planning, executing, and checking. The additional codes were left as other.

Table 3.6: Orienting Phase Codes

Code
Identify Givens
Identify Givens -Variables/Properties
Identify Givens – Assumptions
Identify Givens – Assumptions - Dynamic
Identify Givens –Assumptions - Static
Identify Givens – Assumptions - Uniform distribution
Identify Givens – Assumptions - Heterogeneous distribution
Identify Goals
Identify Constraints

Table 3.7: Planning Phase Codes

Code
Action- General Approach - Control Volume
Action- General Approach - Set up experiment
Action- General Approach - Controls problem
Action- General Approach - Two Zone
Action- General Approach - Porous Media
Action – Categorize
Action - Match to analogous problem
Physiology of bee temperature regulation
Anticipate question

Table 3.8: Executing Phase Codes

Code
Apply **conservation** principle
Conservation - Energy balance
Conservation- Mass balance
Identify modes of heat transfer
Identify Mode -Conduction
Identify Mode - Convection
Identify Mode - Radiation
Identify Mode -Question which drives/negligible
Type of solution method suggested
Solution Type -Analytical – algebraic
Solution Type -Analytical – other
Solution Type - Numerical
Solution Type -Numerical – Finite Difference

Table 3.9: Miscellaneous Codes

Code
Checking
Relate to students
Welcome Challenges
Metacognition
Difficulty encountered
Difficulty - Mass Balance - relate bee movement to problem
Lack of knowledge

In the process of re-coding the transcripts and trying to make sense of the collapsed codes, I realized that on a more general collapsed level with the exception of the orienting category the transcripts were more accurately described by the 5 Step

Engineering Expert Problem Solving Model. In the subsequent rounds of coding, the Orienting category codes were left remained unchanged. However, the three categories of codes were re-categorized based on the 5 Step Process. Additional codes were added as necessary. Chapter 4 explains the results found in the both grounded theory and additional rounds of coding. Examples of the codes are also provided.

Chapter 4: Results

As explained in the previous chapter, the transcripts were first coded using grounded theory methods (Strauss & Corbin, 1998) followed by rounds of coding based on previous problem solving studies. In this chapter, the results from the grounded theory coding are presented first. The next section presents the experts' results on both problems. These results are then followed by differences observed between the two problem types. The final section presents results similar to previous expert-expert studies based on differences in experience with the heat transfer domain knowledge tested in the two problems

GROUNDED THEORY RESULTS

A grounded theory methodology was used in the first round of coding. This means that the transcript was read and coded without trying to apply theoretical framework from previous studies or data outside the study. During this round of coding, three general themes were observed. Professor beliefs about student development and problem solving abilities emerged as unexpected themes early in the coding process. These unexpected themes are discussed first. During the grounded theory coding, different approaches to the complex problem were observed based on differences in expert specialization. These differences in general approach are presented in the grounded theory results section. However, the more nuanced differences that resulted from differences in background knowledge are discussed in the following section with the rest of the second round coding results. The final grounded theory theme is adaptive expertise characteristics. Although these characteristics are consistent with previous work on adaptive experts, this framework was not intentionally applied to the transcripts.

Unexpected Themes

While solving these problems, many of the experts revealed their beliefs about what types of problems are developmentally appropriate for students. The experts were not prompted for this information in either the think-aloud instructions or the subsequent structured interview. Unprompted, most of the experts freely associated their beliefs about problem solving and the types of problems that are appropriate for the typical undergraduate student. They identified the ill-defined complex problem as a good PhD qualifying exam question. For example one expert said:

> So, we're going to give this problem on the next doctoral qualifying exam.
>
> It's probably… It may have appeared on your -- one of your doctoral qualifying exams.

And another said:

> Expert #2: I think it's a problem that… It's a kind… I would say it's a problem that would be interesting to give on a PhD qualifying exam for as a thought -- more as a thought problem than a calculation problem. In other words, you know, "How would you approach this problem?" Not, "How would you solve the problem?" But, "How would you approach the problem? Or, what are the things that are…? What would you have to take into account in order to solve the problem?" As opposed to, "Solve the problem."

None of the experts referred to students while solving the complex problem except to mention that it was appropriate on PhD exam or that the problem was not a good problem for students. However, the experts routinely referred to students while they were solving the textbook problem. They often talked about what was hard for students and where the problem would fall in the sequence of a course on heat transfer. They often revealed what Shulman (1986) calls 'pedagogical content knowledge' (PCK), for example:

> Okay. So, this is kind of a standard heat transfer problem for--for an undergraduate course but toward the end, where we are doing combined mode heat transfer and worrying about what happens. ….
>
> So, uh, everything is there to solve the problem, and I guess my thought process is, gee, I've done a lot of these. [Both laugh.] So, I should be able to work that out. But, um, yeah, it's, uh, it's a fairly standard or straightforward problem; although, it does involve the parallel heat transfer on the outer surface, which is what usually hangs up the students…

One expert pointed out why the routine problem was a good problem and repeatedly emphasized the difficulty of the first problem and that it was just a think problem. The following exchange illustrates the beliefs of the same expert. Throughout the interview he repeatedly explicitly and implicitly communicated his belief that the second problem was too difficult for students (undergraduates) and that the textbook problem was a good "accurate" problem. While solving the complex problem Expert 2 said:

> Expert #2: Okay. Let me ask you, what level -- what level of -- what level of expertise or understanding of transport properties would this problem [the complex problem] be given -- would this be given to? Or just would it just be given to a researcher?
>
> Interviewer: It's been given to students, but for right now for understanding it, like, to a researcher or, you know, to an expert.
>
> Expert #2: Yeah.

Interviewer: Obviously, when we give it to students, their level of -- their level of understanding the system is different.

Expert #2: Yeah. I mean, I immediately see -- I immediately see it as a really pretty complex problem --

Interviewer: Okay.

Expert #2: -- you know, to me. And to me, to me, I would say it's, I guess, I would prefer… I guess, if I -- if I were… I would prefer to come up with a problem that was a little less complex in geometry.

Interviewer: Mm-hmm.

Expert #2: Whereby, that the students could probably come closer to solving it … than this one [complex bee problem].

Interviewer: [laughs] Okay. Yeah.

Expert #2: I see it as, you know, a great problem. I mean, because it's a problem that needs to be solved if you're going to solve, if you're going to look at bee colonies and things like that, study bee colonies. But I'd say -- I'd say it's a fairly difficult problem.

And in other exchanges Expert #2 said:

Well, first of all, I would say it -- those kind -- well, when students start out -- when students start out, they have to have, you know, simple problems, and I would say the second problem was. Even some might be simpler than that, but that's a really good problem. The second one is a really good problem, because it really, you know, it allows them to separate out and not make the problem too complex. So that's a good problem. But at the same time, the beehive problem is really good, because students need to learn that things are not simple. I mean, that's a complicated problem. I don't know. But that's a complicated problem.

The other thing about this problem, which is different from the other one you gave me is that this one is straightforward and within the accuracy of the information given. It's accurate.

The expert was bothered by the complexity of the problem. Because of the format of the interview, I believe he was classifying these problems as school problems (as opposed to a real-world or a research problem). He clearly articulated the highly prescribed problems are good problems – they are simple and provide all the necessary information. Good problems are not too complicated or complex.

Collectively these statements indicate a belief system that is consistent with the traditional model of science and engineering education that teaches the fundamentals first with an emphasis and practice solving routine problems. Only after the students have a handle on the fundamentals will they be given the opportunity tackle more complex novel problems. Sometimes these complex problems are reserved for a capstone course at the end of their program. The traditional model makes three assumptions about the development of complex problem solving abilities. First, understanding the math, science and engineering content is a necessary prerequisite to be able to solve more complex problems. Second, it is necessary to learn to solve routine problems first. Third, the ability to solve routine problems will transfer to more complex ill-constrained problems. The educational implications of the observed teacher beliefs and the traditional model will be discussed in Chapter 5.

Confirmation of 5 Step Problem Solving Process

During grounded theory coding, the experts confirmed 5 Step Expert Problem Solving Process used in previous VaNTH studies of adaptive expertise (Martin, Petrosino, Rivale, & Diller, 2006b; Martin, Rivale, et al., 2007). Figure 4.1 graphically depicts the five steps of this process previously explained in more detail in Chapter 2:

define the system, determine how this system interacts with the environment, identify the governing principles, identify the appropriate constitutive relationships and then solve. The five step process was also confirmed in the both the steps the experts took to solve both problems and the expert discourse. One of the experts re-iterated this process in the think aloud recall portion of the routine problem:

> the energy balance is the key to the problem. And that's, you know… And--and energy balances are my stock and trade, so, I mean, that's -- I always -- I always go immediately to the energy balance. You know, well, let me -- let me rephrase that. What I do in any problem, irrespective of whether it's that one or this one or any other problem, is I ask myself, what are the controlling physical -- what are the relevant physical processes that are happening? In this case, obviously, it's energy, it's heat transfer. If it's a flow problem, the relevant physical processes might be the conservation of mass or the conservation of momentum. Conservation of energy may not be necessary, but what I look for are, what are the relevant physical processes for which we have to categorize, for which we have to write the pertinent conservation relations, or non-conservation if that's appropriate? So, uh, that's the first thing I look at is, what is the character of the problem? And the character of the problem in this case is it's steady state. It's, um… There's heat conduction, convection, and radiation. And at a given surface, at the outer surface, those things have to match up. So there, it's easy enough to write then the energy balance equation.

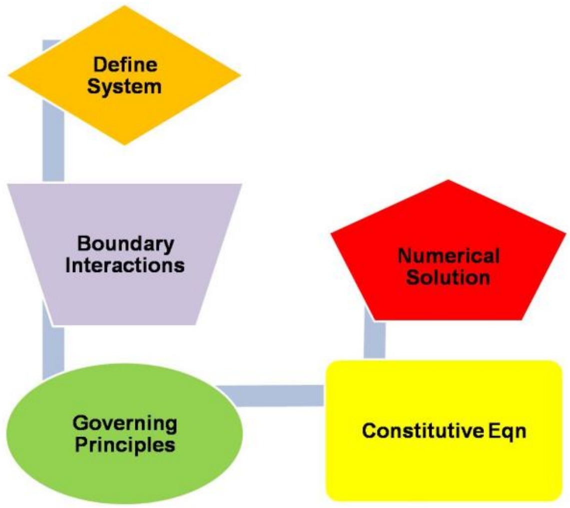


Figure 4.1: Five Step Expert Engineering Solution Process

In general, experts followed this process in both types of problems. Figures 4.1-4.3 are representative of the problem solving process used by two of the experts on the complex problem. Although the general process was confirmed the order of the process was not always sequential. The 5 Step Process was also missing one key step that was observed in the complex problem. There was an orienting/understanding the problem phase that proceeded the *define the system phase* in the complex problem. This difference was not observed in the routine problem. In the routine problem, the first step for all seven of the experts was to draw diagram of the system. Although the experts drew diagrams in the complex problem as well, it was not the first step. It was preceded with efforts trying to understand the problem.

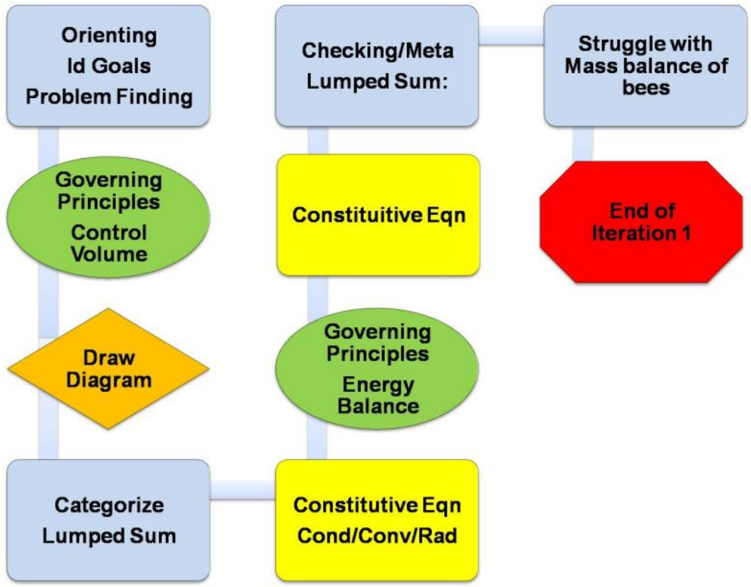


Figure 4.2: Expert 1 (Iteration 1)

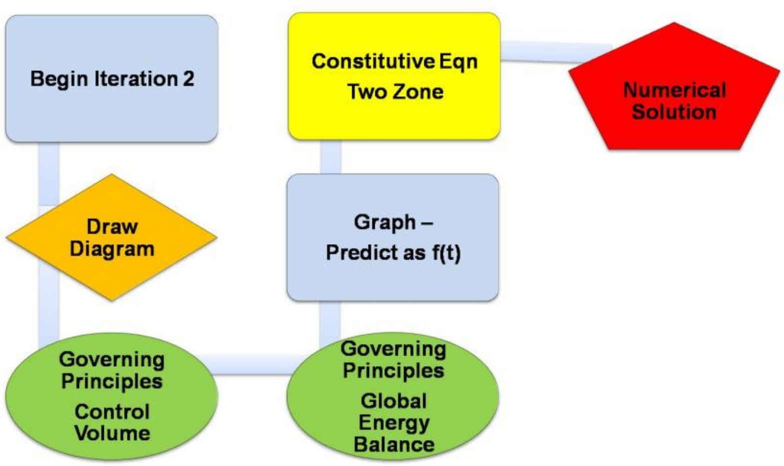


Figure 4.2: Expert 1 (Iteration 2)

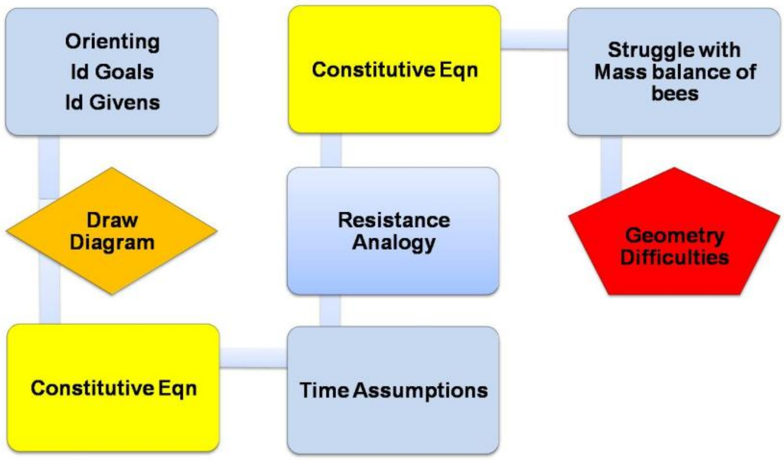


Figure 4.4: Expert 2 Complex Solution

Another major difference is the fact that the *define the system* phase was not trivial in the complex problem. A more cyclic process was observed especially with Expert 1 and Expert 2 who both ranked high in related experience and background knowledge. The process was more automatic in the routine problem. All but one of the experts in the high experience and high specialization category (see Table 4.1 for a review of the categories) immediately recognized the routine problem and its solution path. For example:

> Okay. Ah, good, furnaces. Oh, all right. Now I can…I can identify now. …
>
> Okay. Well, this is, uh, it's not unlike the previous problem, except much simpler….
>
> …this is a straightforward, steady state, heat conduction problem with a boundary condition that essentially the whole problem should be solvable by, uh… I don't even really have to write a differential equation for this.

Specialization Differences

Table 4.1: Expert Experiences

	High Experience High Specialization			High Experience Mixed Specialization		Medium Experience Mixed Specialization	
	Expert #3	Expert #1	Expert #2	Expert #4	Expert #5	Expert #7	Expert #6
Years Teaching	High > 30	High > 30	High > 30	High > 30	High > 30	Medium 10-15	Medium 10-15
Transport Classes	High > 80	High > 80	High > 80	Medium 10-15	None	Medium 10-15	Medium 10-15
Heat Transfer Research	Yes	Yes	Yes	Some	None	Some	None
Porous Media	High	None	None	Some	None	Some	None

There were significant differences in the overall general approaches taken on the complex beehive problem. The problem is ill-defined which increases the number of approaches that can be taken to correctly solve the problem. Most of the experts took a global more macroscopic approach to the problem which is more typical in engineering problem solving – defining the system in terms of global inputs and outputs. However, two experts solution started from the prospective of the bee – a more microscopic approach. It is interesting to note that one of these experts was the only biomedical engineering in the sample and thus the only expert with significant knowledge of physiology and metabolic processes. The other expert that started from the perspective of the bee took a finite element approach which is a numerical method that breaks the system into a grid with neighboring grids interacting with each other.

The other five experts started from more of a global perspective, looking at the general energy inputs to and from the hive. However, the two experts in the sample who conduct experimental research eventually took a more experimental approach to the problem. They planned to use strategically placed thermocouples and get an experimental answer to whether genetics played a role in thermal hive stability. There was only one expert with experience in heat transfer through porous media. The expert who wrote this problem classified the problem as a heat generation through porous media problem. (See next section for the complete porous media solution generated by the expert that wrote this complex problem.) This expert's solution was the most routine-like of the all the experts in the sample.

Thus, specialization and past experience had a significant impact on the experts' problem solving process. The approaches each expert took were highly dependent on their own experiences and knowledge base, and significantly paralleled the methods each expert took in their own research.

Adaptive Expertise

Most of the experts displayed characteristics associated with adaptive expertise like welcoming challenges and being metacognitive. There was only one expert who voiced affective resistance to the complex problem; since this was discussed at length in the *Unexpected Themes* section it is omitted here. Examples of the welcoming challenges were voiced in their excitement about the problem:

> *I*'d want to do some research on that. In fact, you may -- I may end up doing that just because I'm kind of intrigued with it.
>
> Wow! That's an interesting [article].
> Okay. I may have to read that five times to understand what it says
>
> oh, my gosh-"the process by which bees are able to regulate the temperature of their hive." Um…[mumbling] Okay. This is an interesting problem. [both laugh] I've never thought of this before. Okay. Yeah, I mean, I would actually… I mean, I would be interested in knowing, um… You know, I'd love to go study the diverse colonies versus uniform colonies.

These were the experts that took the most time in solving the complex problem. One expert even followed up to get the complete article so he could think about it more because he was so intrigued by the challenge.

All of the experts exhibited examples of metacognition. The recorded transcripts showed more evidence of metacognition when the experts were solving the complex problem. Two of the three experts who were unfamiliar with the routine problem also showed evidence of metacognition. These experts had to generate the solution compared to the experts who were able to rely on prior knowledge and teaching experience with the problem. This makes sense because the experts familiar with the problem had little reason to check there own understanding or problem solving process in the routine problem.

Expert 1 showed the most evidence of metacognition. First, he completed two iterations of the first problem because he realized his assumptions were not validated and he was not answering the question posed. This is what he said as he was deciding tahat his first attempt was incorrect.

> Yeah. I'm beginning… Now, the more I look at the -- ***the more that I look at it, the more I'm beginning to question whether or not you really can treat this as a -- as a lumped system,*** because if the idea is that you can warm the hive up by congregating more bees in the -- in the area that you are trying to regulate,

> then maybe you have to really treat this as if it were an object that could have a temperature distribution in it. Kind of, for example, like a sphere with, uh, -- a sphere with a temperature gradient along it, where bees can -- bees can move from region to region within the sphere, uh, and thereby change the rate of heat generation.[Time: 0:15:00]Yeah. I think, I think I really would have to do that. Because if I treat it as a lump parameter, then that really doesn't… If I treat it as a lump parameter and I don't allow bees to flow in and out of the hive, then it, um, it masks that--that issue. Okay. So, am ***I allowed to back up?***

He verbalized twelve metacognitive instances. The following instances are the most illustrative:

> ***The part of this that's still bothering me is***, when I go back and I read the introduction to this thing, it says, "It has been shown that different genetic lines of bees have varying capacities for fanning action with their wings and may also have varying thresholds for turning on and off the fanning activity to change local hive environment." [Time: 0:30:00] Um… ***How I would actually incorporate that -- those specific things into this model that I've envisioned, uh, that's an interesting question that I haven't got a good answer to***….
>
> ***Let's see. So, let me make another note here. Question: How to incorporate the fanning action and control thresholds of the bees?***
>
> ***Now, the question about the threshold, that's a trickier question, because that's non-linear.*** Well, the whole damn thing is non-linear, to be perfectly honest, but the threshold question says that the -- that the change isn't -- doesn't happen. That is, the H varies with temperature***. I'm going to make a note here. That's another thing that you'd have to figure out. H varies with temperature, because higher T goes to faster bees, faster fanning.***
>
> You know, what are the things that we know and don't know? It looks like we could, you know, figure [that] out. I mean, those are all parameters we can definitely find out or measure.

Expert 5 was able to generate a solution to the routine problem although he had little experience in heat transfer. Like Expert 1's second iteration in the complex problem, Expert 5 drew two diagrams in the routine problem. He drew one diagram as he was reading the problem. Once he realized his diagram was not really helpful at representing what was really going on he drew a second diagram as well. (This is explained further in the following section.) Expert 5 was focused on figuring out what was going on in the routine problem:

> So, I tend to always start off problems as soon as I have any idea. Drawing a figure helps tremendously in visualizing.
>
> Here's what we don't know. Call that t-2. Tend to always want to make sure. So, maybe the figure is the most critical thing in understanding what's happening.
>
> You know, what are the things that we know and don't know? It looks like we could, you know, figure [that] out. I mean, those are all parameters we can definitely find out or measure.

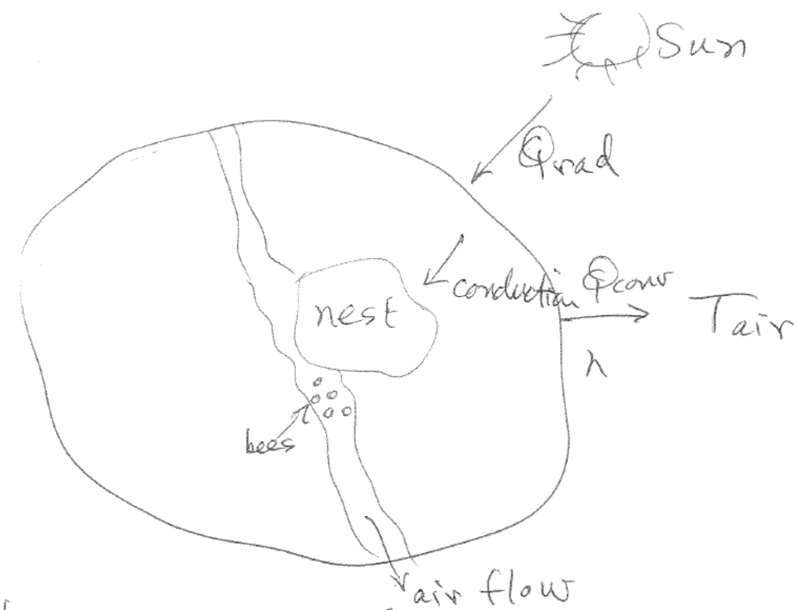
RESULTS BY PROBLEM TYPE

Complex Problem

The complex problem is interesting for a couple of reasons. First, it is ill-defined with complex geometry and numerous dynamic and undefined properties. Second, the nature of the problem lends itself to both top-down aggregate and bottom-up more agent-based solutions. The expert who wrote the problem took a top-down aggregate (finite difference) solution path. The following section describes author's expert solution to the complex bee problem given in this study (Diller, 2006).

> *Define the System*: The system of interest consists of a solid hive with a porous passageway structure through which bees and air can pass. Undoubtedly, the passageways are quite tortuous, so the geometry is quite complex. Apparently, there is a localized nest area, or areas, wherein the temperature regulation is most critical. There are likely bees within the nest area that do not leave during the process to be analyzed, so they can be included in the system mass.

Environmental Interactions: The system has various interactions with the environment. Internally, when the temperature is higher than the target the bees flap their wings to create convective air flow within the passageways to provide cooling of the hive structure. Conversely, when the temperature is lover then the target, the bees congregate in the nest area to provide a collective metabolic energy source of het which is transmitted to the nest. Another physical boundary of the system is the external surface of the hive where it is exposed to the atmosphere. At the exterior surface there may be convection and/or radiation depending on environmental conditions and the location of the hive with respect to surrounding structures. In conjunction with these external conditions there may be a significant overall temperature gradient imposed on the hive between the surface and the nest, which is presumed to be located toward an interior site. A sketch of the system and environmental interactions is shown below. (Figure 4.5 is the author's diagram of this system.)



The bees can be a local metabolic heat source or a source of convective air flow through the passageway

Figure 4.5: Author Solution Diagram

Governing Principles and Constitutive Equations: The governing law for describing the thermal behavior of the hive and nest is the conservation of energy. As a first approximation this system can be modeled using the Pennes equation that describes blood flow through tissue that produces a distributed metabolism within. The Pennes equation assumes that there is full thermal equilibration between the blood and the local tissue. This assumption may not be valid for the air flow through the hive however. An alternative approach is to modify the Pennes equation so that incomplete convective exchange occurs between the flowing air and the hive. The conservation of energy equation with appropriate constitutive components might look like this:

$$\rho c \frac{\partial T}{\partial t} = k\nabla^2 T + (\rho c)_b (T_a - T) + Q_{met}$$

Solution Plan: It would very helpful to get some added information about the size of the passageways in a hive and what kind of air flow velocities bees can generate to make an estimate of the convective heat transfer coefficient for air flow therein. The boundary conditions are convection and radiation on the external surface of the hive and convective and heat generation distributed internally within the nest volume of the hive. It is difficult to say what the initial conditions should be since the hive is in existence on an ongoing basis and there will continually be an internal gradient. Probably the best approach would be to find out what the optimum thermal distribution is and use that for the starting point. The hive variation form the optimum in response to defined perturbations could be evaluated.

Added information that should be obtained includes data on the solar radiation constant for the geographic location of the hive, typical wind velocities for that region, and how much metabolic energy bees can generate per unit volume and time. Further, the thermal properties of the hive are needed, and it will be necessary to determine if the porosity of the hive is large enough to compromise an assumption of conduction through a homogeneous medium. If it is necessary to include conduction around the hive passageway structure the geometry becomes horrendous, and a finite element model would have to be implemented with a lot of detail about the passageway geometry. The differential equation that results from this model is likely to be nonlinear due to Pennes convection term and possibly due to hive geometry, requiring a numerical technique to solve.

The experts in this study took three general approaches to this problem: the global macroscopic approach taken by the expert who wrote the problem, a microscopic approach that focused on the perspective of an individual bee first, and an experimental approach. The diagrams drawn by these two experts help illustrate the differences. Figure 4.6 shows diagrams drawn by experts who took the global macroscopic approach and Figure 4.5 shows the diagrams drawn by the two experts who start from the microscopic perspective of the bee. Two experts took an experimental approach that set up an experiment to test how the two different groups of bees (a genetically diverse population of bee and genetically homogeneous population of bees) affected internal hive temperatures using thermocouples and an experimental method. The experts who took the experimental approach took a macroscopic approach to modeling energy flow in their experimental set-up.

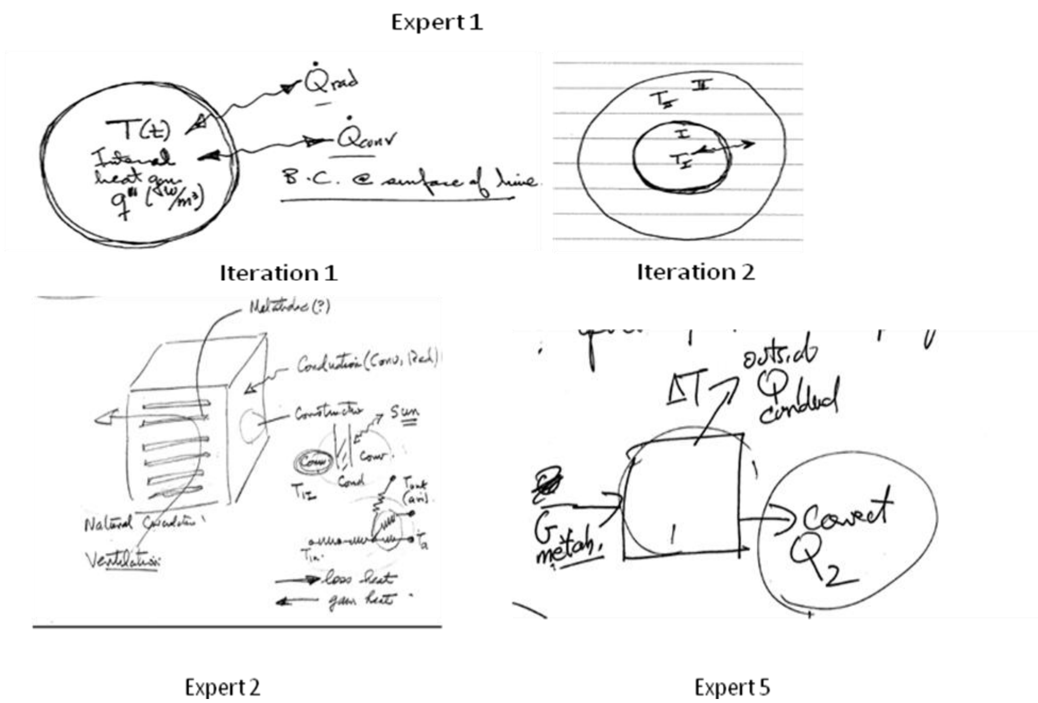


Figure 4.6: Diagrams from Global Macroscopic Approach

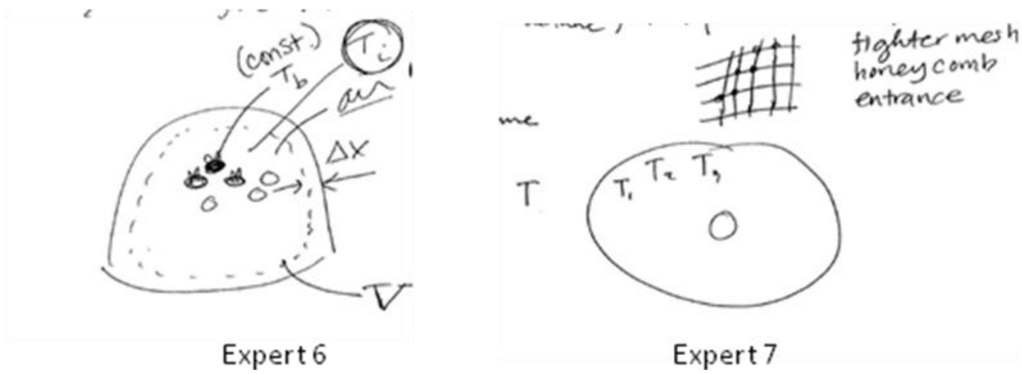


Figure 4.7: Diagrams from Microscopic Agent-based Approach

Of the three experts that took the macroscopic approach, Expert 3's solution most resembled the solution given presented earlier. He was not familiar with the Penne relationship and set up a finite element solution path. Expert 1 initially took a control volume approach and categorized the problem as a lumped capacity problem. After generating the appropriate constitutive equations he questioned the lumped capacity assumptions and started a second iteration of the problem eventually deciding that a numerical solution was necessary. Both Expert 1 and Expert 2 ran into difficulty when they tried to do a mass balance on the bees. This is illustrated in the following think aloud passage:

> So first of all, I would try to characterize it as kind of a classical heat transfer problem. And then, um, now, the question … the question that I'm asking myself in my mind is, what, um… I've got to tie this back to the original question, which is, "How would you quantify the transient hive temperature to ultimately determine whether or not genetic diversity among bees helps stabilize hive temperature. Your job is to determine an approach to analyzing and modeling a process by which bees are able to regulate the temperature of their hive." ~~ Yeah. I'm beginning… Now, the more I look at the -- the more that I look at it, the more I'm beginning to question whether or not you really can treat this as a -- as a lumped system, because if the idea is that you can warm the hive up by congregating more bees in the -- in the area that you are trying to regulate,

> then maybe you have to really treat this as if it were an object that could have a temperature distribution in it. Kind of, for example, like a sphere with, uh, -- a sphere with a temperature gradient along it, where bees can -- bees can move from region to region within the sphere, uh, and thereby change the rate of heat generation.

The Diller solution avoided this complexity by assuming that there were some bees that did not leave the system, thus including them in the system.

The other two experts started from the perspective of an individual bee and then thought about how individual bees would influence heat transfer and thermal stability. They got stuck at the intersection of trying take go from the agent based perspective they started with to a more global energy balance.

> So we have the conduction from the bees to the air inside, radiation, or we can neglect that, conduction from the bees to the inside air, um, which depends on the physiology of the bee, which is going to vary depending on genetically alike or genetically dislike bees, in terms of wing span, flap velocity, etc., and then you're going to have conduction from the outside as well, depending on the temperature outside, thickness of the beehive, and so forth. So yeah, I just - I couldn't - I couldn't put it all together into an actual equation, but those are the most important components.

So all four of the five experts (excluding the two that took the experimental approach) struggled at the intersection of the aggregate and agent based approach.

Routine Problem

The expert solutions to the routine problem were quite similar with only minor differences in approach, time to solution, and final solutions. Although, most of the experts (6) set up the problem correctly, none of them carried the solution out to a numerical answer. All six of them stopped once they set up an algebraic solution with one unknown. They all started drawing a diagram as they were reading the problem and recording the givens.

Expert 7 was not able to remember or generate the constitutive equations (Table 4.3 summarizes the process but see the next section for further elaboration). Two of the experts recognized the problem immediately and two of them recognized it quickly after they started reading the problem. Table 4.2 summarizes the approach taken by these four experts (3 task experts and the one expert with less transport teaching experience). Table 4.3 summarizes the approach taken by the other three experts. The only difference between these groups was that the domain expert (Expert 5) and the biomaterials engineering expert (Expert 6) had to generate the constitutive equations and the solution, they did not recognize it. The next section validates this claim in more detail. Only these two domain experts mentioned units as a checking strategy. They all started drawing a diagram as they were reading the problem and recording the givens. Many of them (4) took queues from given variables and constants for example:

> Known brick thermal conductivity and surface emissivity, which immediately tells me that the person who put the problem together wants me to worry about radiation from the outer surface as well as conduction.
>
> Stefan-Boltzmann constant, which I have no idea how that enters, because that's -- that's for radiation heat transfer, I guess, but I don't remember, because I literally have never had a course.
>
> "The brick has a thermal conductivity of 1.2 W/m•K and a surface emissivity…" Ugh. That means they want us to do radiation. [chuckles] Um, of 0.8. Oh, my gosh, it's been so long.

Table 4.2: Domain Expert Routine Solution Summary

	Expert #3	Expert #1	Expert #2	Expert #4
Recognize Problem	Immediately	Immediately	As solving	As solving
Orienting	Read Assumptions from givens Relates to ugrad	Skim	Read Assumptions from givens	Read
System & Interactions	**	Diagram	Diagram	Diagram
Planning & Sense making	List givens verbally Categorize: 1D & SS **Diagram Rad & Conv in parallel	Label givens Categorize: S.S. Determine given/unknown temps	Label & check givens Resistance diagram Rad & Conv in parallel	Label givens S.S.
Governing Principles	Implicit	Overall energy balance	Implicit	Implicit
Constitutive Equations	Constitutive equation conduction only	Constitutive equation radiation convection conduction	Constitutive equation radiation convection conduction	Constitutive equations radiation convection conduction
Solution	Sets up correct solution	Sets up correct solution	Sets up correct solution	Sets up correct solution

Table 4.3: Routine Summary

	Expert #5	Expert #6	Expert #7
Recognize Problem	Generates solution	Generates solution	Does not solve
Orienting	Read	Read	Read Re-read
System & Interactions	Diagram	Diagram	Diagram
Planning & Sense making	Label givens Queued by S.S. Stephen-Boltzmann -> rad What happening?	Label givens Checks to see S.S. Emissivity queues rad	Label givens Not queued by S.S. Can't remember emissivity
Governing Principles	Diagram energy flows Global energy balance	Labels heat flows Rad & conv in parallel	No energy balance
Constitutive Equations	Generates constitutive eqn radiation convection conduction	Constitutive eqn radiation convection conduction	Attempts constitutive eqn correct conduction sets equal to heat capacity Attempts to generate rad eqn
Solution	Checks units Generates correct solution	Cancels units Sets up correct solution	Stuck at constitutive eqn Does not solve

The Domain Expert Example

Expert 5 is the domain expert with over 30 years of engineering teaching experience, but little experience with heat transfer. He had not even taken a heat transfer course in graduate school. Thus, even in the case with the routine problem, he is an expert solving an unfamiliar problem. Table 4.4 explains in further detail his problem solving process from his think-aloud transcript.

Even though Expert 5 had little heat transfer experience, he was almost able to generate the correct solution. Table 4.4 gives his segmented transcript and a description of his solution steps in the routine problem, he had to generate the conduction, convection and radiation constitutive equations. He was obviously familiar the transfer constants coefficients because he was able associate them with the conventional variables (i.e. thermal conductivity is represented by k). The fact that he was generating as opposed to recalling these equations is most apparent in his discourse as he was writing the conduction rate equation:

> It's going to allow me to hopefully determine that, because… I think just a K change in temperature [in] respect to distance is going to be related to what's the… I don't what the right terminology is for, what's the energy moving at any point? Because it's got to be the same everywhere. What's coming here, has to be here, here, and here. So, linear gradient, that's K.

He did not know the terminology but he knew the energy difference was driven by a temperature gradient. The Stephen-Boltzmann constant queued him that radiation should be considered. He also thought he remembered that radiation had a fourth order power relationship but he was uncertain and crossed it out. He nearly generated the correct equation. However, he did not realize that all three of the rate equations were per unit area. Since the problem was at steady state, the cross sectional area could be dropped since it canceled out.

Table 4.4: Expert 5 Routine Problem Transcript

Expert 5 Routine Problem Transcript	***Action Description***
So, I tend to always start off problems as soon as I have any idea. Drawing a figure helps tremendously in visualizing.	Draw diagram
So, ambient air is at 25˚. I don't know if this is significant, but this is a brick wall that's .15 centimeters. The brick has a thermal conductivity, so I tend to want to, as much as I can, assign symbols to things to make it easy to -- rather than words. And a surface emissivity of 0.8.	Givens
Now's when I wish I had taken a heat transfer course, because I never took one and I never taught it.	Affective
Using steady state conditions, so that sort of makes a big difference. A much easier problem to solve when I see that.	Queued by steady state
An outer surface temperature of 100˚, so I'd assume it means you're right here. It's 100˚C. Inside, it's hotter. This is a furnace. Okay.	Label given temperature
Free convection heat transfer to the air is adjoining the surface, so there's a heat transfer coefficient there flowing by. And h equals 20. Okay	Write given heat transfer coefficient
Stefan-Boltzmann constant, which I have no idea how that enters, because that's -- that's for radiation heat transfer, I guess, but I don't remember, because I literally have never had a course. That's from a different undergraduate program.	Stephan-Boltzmann queues radiation Affective
Okay. So, I don't know if I'll need that.	Metacognition
So, what is the brick inner surface temperature? Okay. Okay. So, we're talking about… Here's what we don't know. Call that t-2. Tend to always want to make sure.	Identify question asked
So, maybe the figure is the most critical thing in understanding what's happening.	Draw another diagram (Define system) Metacogniton
So, there's some temperature gradient.	Draw temperature gradient
So, really, the figure that's really important is that this is 100˚, this is a t-2. Out here the air is 25˚.	Label Diagram

Expert 5 Routine Problem Transcript Cont.	*Action Description*
Now, we've got some heat transfer due to that.	Identify energy transfer: convection
And then I've got some radiation, I guess, though, it's 100˚C. I don't know how significant that is.	Identify energy transfer: radiation
And I have thermal conduction through the wall. So, the idea is that there would be some temperature gradient through the wall. Whatever heat goes here. And…and so what… So, this is 100, what the heat loss here.	Identify energy transfer: conduction
Then, I'd do an energy balance across the wall.	Governing Principle: Global energy balance
It's going to allow me to hopefully determine that, because… I think just a K change in temperature [in] respect to distance is going to be related to what's the… I don't what the right terminology is for, what's the energy moving at any point? Because it's got to be the same everywhere. What's coming here, has to be here, here, and here. So, linear gradient, that's K.	Constitutive equation: Generate conduction equation
And so that energy at any point, including here, has to be related to the 100 minus 25. Some heat transfer coefficient.	Constitutive equation: Generate convection equation
And then there may be some 100 minus… Well, I think it's got to be absolute temperature. Don't worry about that. I'm going to erase to a power. So, you know, so, 378[?] minus 298, because I think it's to the fourth, times emissivity. And that's probably where this constant comes in, this s constant on both.	Constitutive equation: Generate radiation equation
If I was trying to get a number, I'd probably look at units to see if that makes sense. So, I tend to use units a lot to see if the terms make sense. And I'm doing this per unit area. Right? That would be my basis. On the outside putting numbers in, I guess, to me, that's the best I can remember heat transfer.	Metacognition Checking Units

Expert 5 drew two different diagrams as he was solving the problem (see Figure 4.8). He immediately started to draw the first one as he read the problem and after he finished reading the problem and identified the question and the unknown he was solving for, he started drawing a second diagram that helped him make sense of the problem. He identified the figure as the critical step in the problem. It is interesting to note that his first diagram was almost identical to the diagram drawn by Expert 7 (see Figure 4.9.) who was also unfamiliar with the problem. The second diagram he drew in as he was trying to understand the problem was almost identical to the diagram drawn by Expert 3 (see Figure 4.10). Expert 3 was the only expert familiar with both problems who even solved the complex problem as if it were routine.

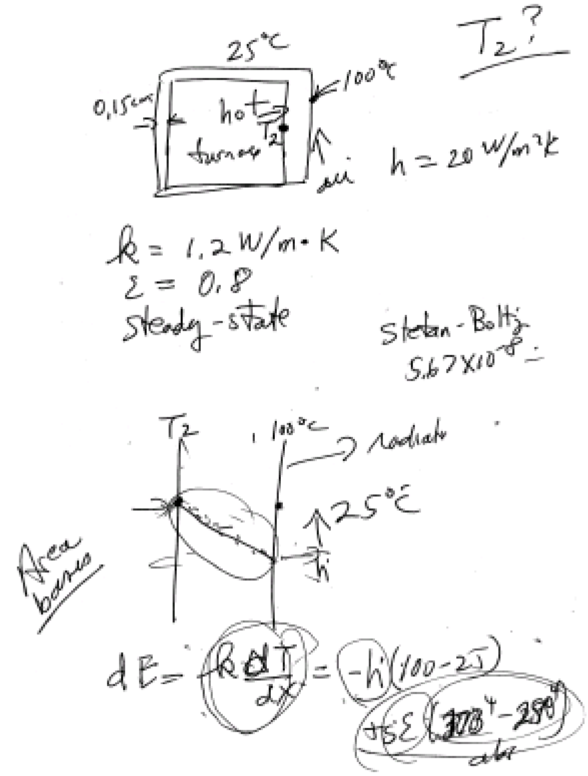


Figure 4.8: Expert 5 Routine Problem Solution

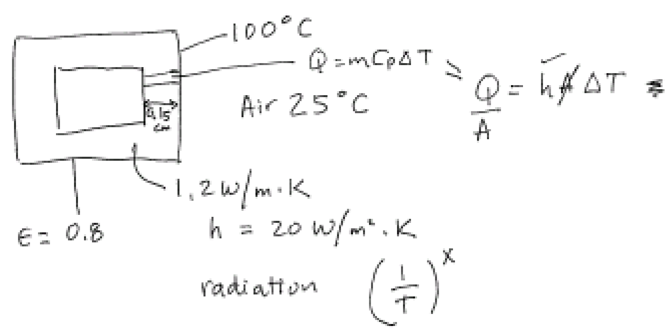


Figure 4.9: Expert 7 Routine Problem Solution

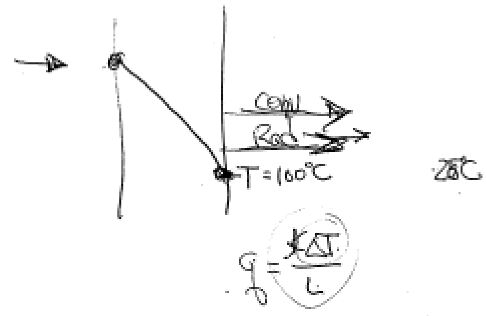


Figure 4.10: Expert 3 Routine Problem Solution

DIFFERENCES BASED ON PROBLEM TYPE

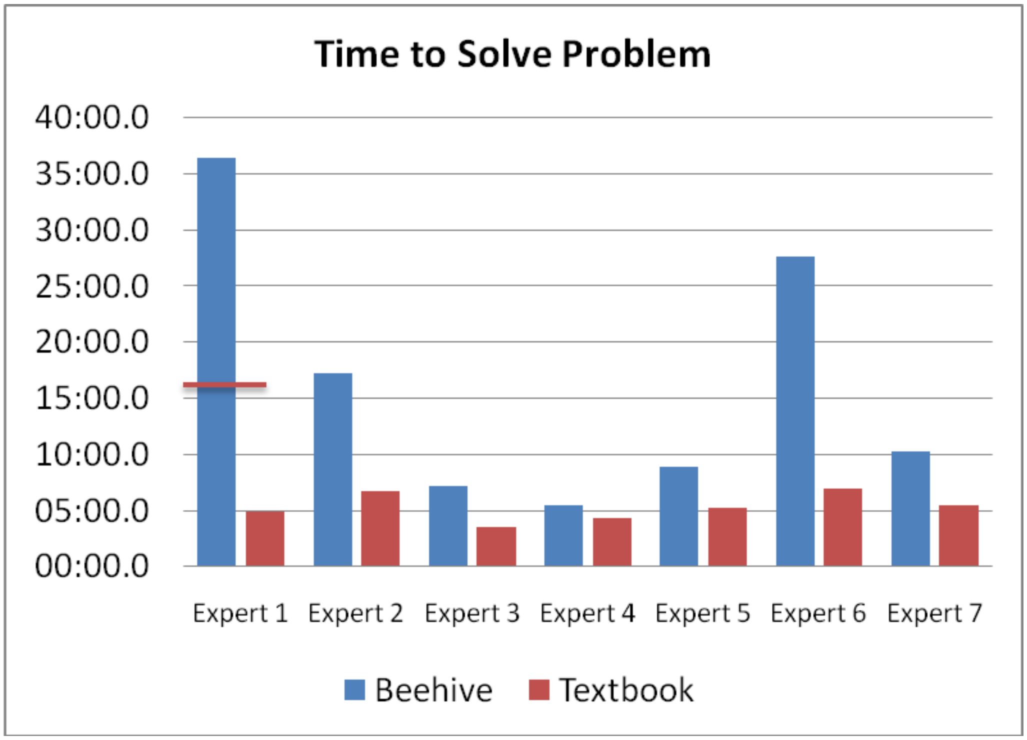
This problem was challenging for all of the experts with one exception. The problem was much more straightforward to the expert with significant experience heat transfer in porous media systems. The expert who generated the complex problem classified the problem as a heat transfer in porous media problem. After solving the problem, all of the experts were asked if they thought the problem was hard, and if so, what was hard about it. They found it difficult because it was unfamiliar. Many of them had never thought about transport in “living stuff” before. They all found it hard to link the bees to the transport model. They also found it hard to determine the geometries, the properties and the spatial distribution of those properties. Initially, most of the experts tried to make simplifying assumptions about the geometry and the properties in order to simplify the solution. However, then they questioned these simplifying assumptions when they returned tried driving question about the influence of genetic diversity in bee hives. One expert commented that, “it’s hard to set up a model when everything is a variable”.

The engineering experts with less heat transfer experience mentioned that they (like students) always found transient problems difficult. Another expert captured the essence of the problem selection well when he said;

> Well, I think the beehive problem is a good problem to understand how somebody attacks or sets up a problem, because you're not asking for a numerical answer. You're asking for a strategy. And you're asking for someone to take a word problem and reduce it down to something that now is amenable to being solved. And I know from what I learned about problem solving is that it's hard for students. You have to take a word problem, and then you have to reduce it to its elements. And it's also a good problem, because you have to figure out what part to read.

Time

On average, the experts spent significantly more time ($p = .019$) solving the complex problem than they did on the routine problem, an average of 16 minutes compared to 5 minutes respectively, see Figure 4.11. Expert 1 completed two iterations when trying to solve the beehive problem. He was the only one to do this. The red line indicates the time break between the two iterations.



* The read line indicates the iteration split for Expert 1.

Figure 4.11: Solution Time

There are two additional limitations that must be considered. Individual differences based on loquaciousness are common in verbal report data, and the complex problem statement is much longer than the routine problem statement (448 words compared to 92 words). Since there were differences in whether the expert read aloud or read silently and the fact that some experts started solving the problem as they were reading it, the average time to read the problem could not be subtracted from the total time on each problem. As a proxy, I timed myself as I read each problem at a conservative pace and subtracted this time from the total time on each problem. There was a difference of about 2 minutes in the time it took to read the problems out loud.

Table 4.5: Adjusted Time by Problem Type

	Beehive	Beehive*	Textbook	Textbook**
Expert 1	36:27.5	33:49.5	04:50.8	04:12.8
Expert 2	17:11.4	14:33.4	06:45.2	06:07.2
Expert 3	07:13.6	04:35.6	03:32.8	02:54.8
Expert 4	05:29.5	02:51.5	04:16.8	03:38.8
Expert 5	08:50.6	06:12.6	05:11.9	04:33.9
Expert 6	27:37.2	24:59.2	06:56.1	06:18.1
Expert 7	10:19.2	07:41.2	05:29.7	04:51.7
Average	16:09.9	13:31.9	05:17.6	04:39.6
Median	10:19.2	07:41.2	05:11.9	04:33.9

* Adjusted by 2:38 minutes

**Adjusted by 38 seconds

DIFFERENCES BASED ON RELATED EXPERIENCE AND BACKGROUND KNOWLEDGE

The largest difference between the two knowledge groups was whether they categorized the problem or not. Three of the four task experts categorized the routine problem and talked about trying to categorize the complex problem (see Table 4.6). The rest of the experts did not do this. They recognized similar problem conditions like whether it was steady state or transient, but they did not try to categorize the problem. In the routine problem they categorization quickly queued the solution path. They knew the problem would eliminate the need to set up a differential equation. In the complex problem they were categorizing the problem in the as they were generating the appropriate model or the appropriate solution.

Table 4.6: Task Expert Categorization

Complex Problem	Routine Problem
So first of all, I would try to ***characterize it as kind of a classical heat transfer problem***. And then, um, now, the question	Uh, I know that in a ***one-dimensional heat transfer problem that's steady state*** that the amount of heat transfer per unit area on the inner surface is equal to the amount of heat transfer on the outer surface, and that sort of gives you the clue of how to handle this
I see this as analogous to a problem, a kind of a classical problem in heat transfer of the heating or cooling of a ***lumped object*** in which there is some internal heat generation	…this is a ***straightforward, steady state, heat conduction problem*** with a boundary condition that essentially the whole problem should be solvable by, uh… I don't even really have to write a differential equation for this.
You know, in the summary, I think I would set up a… As I said, I would assume at least for this point for this to be a ***quasi steady state problem*** with long-term variations and long-term…	Okay. So, this is kind of a ***standard heat transfer problem*** for--for an undergraduate course but toward the end, where we are doing ***combined mode heat transfer*** and worrying about what happens
Other than the fact that there is some sort of activity going on inside that generates heat, it is not something that regulates itself or is regulated. It's just going on. Okay. So, I started this by saying, ***how do we model problems like that, and what would be the analogous model here?*** So, the first thing that occurred to me is that I could characterize this as a spherical particle, spherical object, and go through the usual energy balance type stuff with boundary conditions and some initial condition	Okay. Sure. Uh, well, uh, I looked at it, and first of all, I paid special note to the fact that it said "under steady state conditions." So again, I'm trying to categorize the problem. Because there is a wall, there is heat conduction through the wall, and as always, the energy balance is the key to the problem. And that's, you know… And--and energy balances are my stock and trade, so, I mean, that's -- I always -- I always go immediately to the energy balance.
I was thinking about it in terms of a ***standard sort of heat transfer fluid mechanics problem***, where you want to look at the heat trans- -- heat balance, mass balance on the entire system. And so, ***it gets down to analyzing it in the same way you do most problems like this for porous media heat transfer***.	

The experts were asked about is they could think of another problem that would be analogous to the bee hive problem after they solved the problem. Table 4.7 gives the expert answers to this analogous problem question (Expert 2 did not answer the question.) The domain experts gave more general analogies: a heat exchanger, a house, and a cup of coffee. The task experts gave more all focused on the fact that the problem involved a heat generation component and porous media.

Table 4.7: Analogous Problems

	Analogous Problems
Expert 1	Here's one that I can conceive of: possible problem, like, for example, of solidification of, uh, castings for crystallization of materials that are where there's ***crystallization occurring from a continuous phase, because the--the rate of heat generation, if--if--if… I can think of this in crystallization*.** There's heat generation -- there could be -- there could be heat generation occurring as a result of exothermic processes that are going on. And typically when something crystallizes, often, in many instances, it's exothermic. So, there's a problem in which the rate of internal heat generation in the volume has to be represented functionally as a function of the population of crystals, which might be expressed in terms of the density of--of the solid phase versus the liquid phase, something like that. So, I could see some analogy there. Probably less so in metallic materials, because the thermal conductivities are so high it probably doesn't -- the solidification energy probably doesn't affect those things very much. Now the question of where there is some sort of active control mechanism going on, that's … that's a very interesting one. I have no idea where I would find other problems.
Expert 3	Mm-hmm. I've worked on a lot of ***porous media problems with internal combustion inside a plug of porous material***, so it's called submerged combustion. And we've had to model those, and there are a lot of similarities, because you have heat generation by the combustion process, you've got flow in and out, you've got changes in the properties due mostly to the temperature differences in that case. Although, we've done some with varying material properties in the porous material itself. So, you know, that's an analogous sort of problem. I mentioned the nuclear reactor core. Similar sort of problem with heat generation and flow through the system. In some ways, those are simpler systems, because the flow is not dependent on the ambient temperature the way these are, but--but they are similar.
Expert 4	Well, if… Uh, if I was thinking of the bees, you know, and if I was thinking of a mass transfer analogy, you would think of a ***catalys*t**. In other words, I have a packed bed with catalysts, and so if I was doing reaction, uh, then, you know, and so that would be the, uh, the analog of generating mass. Although, yeah, in other words, the catalyst would be part of it. You still have to have the mass source or sink, so you'd also have to have some mass. So maybe a better analog would be, like, a sorbent. So if I have a sorbent in a packed bed and I pass mass to it, it takes the mass out of the fluid phase. Then that would act like a sink or a source depending on which one you were looking at.

	Analogous Problems
Expert 5	Well, in some ways, it's not a lot different from a ***chemical reactor***. You're generating heat by a reaction, for example. You remove ***heat by flow in and out and heat transfer through walls***, so you could say it's probably analogous to that kind of problem, which is the kind of problems that I would teach, you know
Expert 6	Well, I mean, I think of it somewhat similar to ***shell and tube heat exchanger***, because you have a lot of little internal tubes which are like your little internal bees. I mean, except there you would have, I mean, I guess you would have forced convection, um, which you have forced convection with the wings. You can have forced convection through the tubes. And then you'd have each one having, you know, conduction and so forth. So it's – it could be somewhat analogous to that if you looked at it as an unsteady state or transient problem. But, um, other problems in engineering? Nothing that I deal with, so… [laughs]
Expert 7	Any systems like the bee hive problem. Well, I think a ***house***. ... Yeah, a house is a lot like that. We bring in air and take out heat. Let's see, so ***anything with a shell***, that would be important. How about a ***coffee cup***? A cup of coffee. .... That would definitely… You know, why does it cool at a certain rate? And does it stay warmer if you don't ever take a sip from it? [both laugh] And then, what would be the point?

Chapter 5: Conclusions

This study addressed the following two research questions: (1) How do engineering experts solve non-routine complex problems? (2) Does an experts' process solving these types of non-routine engineering problems differ from the processes found in classic expertise research using routine textbook-like problems? This chapter first summarizes the results that address the research questions and the unexpected themes uncovered with grounded theory methods. Then the educational implications of these findings are discussed.

(1) How do engineering experts solve non-routine complex problems?

- In general, this study confirmed the 5 Step Problem Solving Method as an expert engineering problem solving method.
- The experts in this study also solved routine engineering problems outside their expertise or familiarity using this same method focusing on applying general principles prior to addressing constitutive equations and a solution path.

(2) Does an experts' process solving these types of non-routine engineering problems differ from the processes found in classic expertise research using routine textbook-like problems?

- There were observed differences based on problem type and background knowledge.

- The routine problem was more automatic and took significantly less time.
- The experts with higher amounts of background knowledge and experience categorized the problems.
- The level of background knowledge was most apparent in the steps between conducting an overall energy balance (Governing Principles) and writing more problem specific relationships between the variables (Constitutive Equations).

However, the most interesting findings of this study are the unsolicited themes uncovered using grounded theory methodology with the collective qualitative data corpus. The experts in this study unexpectedly revealed strong beliefs about problem solving ability and development in students. They associated the complex problem with PhD students and the routine problem with undergraduates. The educational implications of these findings are discussed in the following section.

EDUCATIONAL IMPLICATIONS

The traditional engineering education system makes the assumption that experience solving routine problems will transfer to ill-structured problems. It also assumes that it is necessary to learn to solve routine problems first. However, it isn't completely understood how different types of problems affect this development. These assumptions are not explicitly tested in this study. However, this study was motivated by the desire to improve engineering instruction by characterizing the desired endpoint.

How do engineering experts attempt these types of problems? How can their solutions inform educational practices?

In the current system, students practice solving lots of routine problems. For a selective few, this method leads to expert-like understanding. Only those that persist are given the opportunity to work on more interesting complex problems. The expert beliefs are consistent with the traditional way engineering education is structured. Students are taught the fundamental principles first by direct instruction lecturing and solving lots of highly constrained problems on exams and homework sets. After they have "mastered" the core content, they are then allowed to attempt novel complex problems. The experts' beliefs found in this study are consistent with the hierarchy of problem types in the mathematics curriculum described by Stanic and Kilpatrick (1988):

> Putting problem solving in a hierarchy of skills to be acquired by students leads to certain consequences for the role of problem solving in curriculum. One consequence is that within the general skill of problem solving, hierarchical distinctions are made between solving routine and nonroutine problems. That is, nonroutine problem solving is characterized as a higher level skill to be acquired after skill at solving routine problems (which, in turn, is to be acquired after students learn basic mathematical concepts and skills). This view postpones attention to nonroutine problem solving, and, as a result, only certain students, because they have accomplished pre-requisites, are ever exposed to such problems. Nonroutine problem solving becomes, then, an activity for the especially capable students rather than for all students (page 15).

The expert beliefs about student development and the appropriateness of problems falls outside of the theoretical 'optimal adaptability corridor' proposed by Schwartz et al. (2005) (See Figure 5.1). The experts in this study exhibited strong beliefs consistent with the traditional educational model that it's necessary to focus on efficiency before students can tackle more innovative problems.

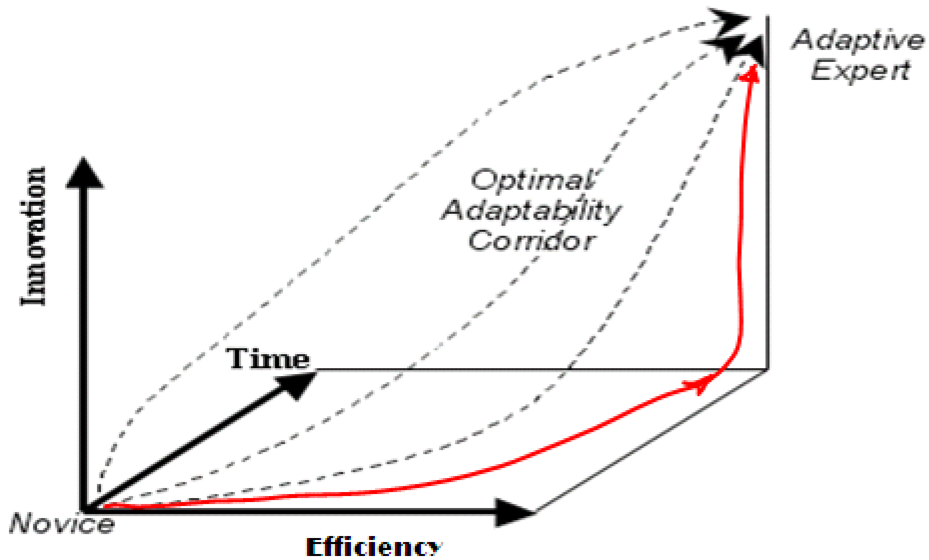


Figure 5.1: Expert Beliefs Trajectory

The expert beliefs are inconsistent with their performance on both types of problems. Even on the routine problem, none of the experts carried out their solutions to a final mathematical solution. They merely set up the problem following processes similar to the 5 Step Problem Solving Method. Even the experts with less specialized knowledge were able to attempt the problems. The experts in this study attempted the problems from general principles first. Only secondarily did they attempt to apply constitutive equations and set up a solution path. None of the experts carried either problem out to a mathematical solution. If this is how experts solve these types of engineering problems, is it necessary for students to have mastered basic math skills and physics equations before taking on more complex problems?

One of the experts in the study articulated this when he gave his ideas about what innovative student performance looks like.

> ***one of the things that really catches my attention is when I have a student come in and explain to me physically what he thinks is going on, and then we talk about, now how do I capture that in terms of writing equations and formulas, so you get a number for an answer?*** … our students today have much less of an intuitive sense of how physical things happen. They are more oriented toward, ***"Let's cut to the chase. You tell me which formulas I have to plug numbers into in order to get an answer."*** So, what I view as innovative is a student who looks first at the problem before they look for, "Where do I plug and chug in order to get an answer?" … But the idea was to put more hands-on really looking at real things and saying to yourself, "How does what I'm studying apply to this thing here?" ***Okay. And so, if I try to characterize the quality that I think is going to -- is going to be observable in a student that's going to become something special as an engineer, I would say I would put that right at the top of my list. This intuitive sense of what's really happening before you start trying to just plug numbers into it.***

In the engineering workplace, Jonassen et.al (2005) found that nearly all problems are complex and ill-structured. If we are going to prepare students to be innovative and technically proficient they program need more practice solving complex ill-structured problems. Students often only encounter these complex ill-defined problems at the end of their four year engineering program because of an under-current belief that they need to have mastered basic math and science concepts first.

Ericsson (2006) has shown expertise is often the result many hours of deliberate practice. He has found that expertise in many domains like music, sports, chess, and problem solving require at least 10,000 hours (approximately 10 years) of practice. The 10-year rule has been shown to be fairly robust across domains (Ericsson, 2006a). Solving engineering problems takes "deliberate practice" just like playing basketball or the piano (Ericsson, 2006). For students, the hours they spend doing homework and studying is practice. A good coach facilitates this practice to maximize performance. Using a basketball analogy, nearly all teams practice shooting layups but they also practice putting it all together in the real time scrimmages. Coaches make their players practice both in pieces and putting it all together. Routine problems can be seen as analogous to a layup and complex real-world problems analogous to a scrimmage. In a previous study one student highlighted this difference when he asked, “you mean you want me to solve this like a real problem in the lab or something, not like homework or a problem on an exam.” Our students have learned how to “play school” well, but we need to make school more applicable to the careers we are preparing them to enter. Students need more practice solving complex real-world problems. It seems unnecessary to make students wait to start this practice only after they have mastered basic math and science concepts. As Schwartz et al. (2005) propose, they should be practicing both types of problems at the same time.

In previous studies, students given practice with both complex and routine problems in challenge-based engineering courses performed higher on innovation measures than students taught using traditional methods.(Martin, Rivale, et al., 2007) The results of these studies combined with the unexpected themes identified in this study indicate that professor beliefs about problems and problem solving need to be factored into reform efforts in engineering education. Future research needs to explore these beliefs more rigorously. If these findings are verified, they do hold promise. Obviously, the engineering professorate is highly skilled in writing PhD qualifying exam questions. They also have experience with problem based learning: the model is very similar to mentoring new graduate students in their research labs. The logical next step is to help direct these skills into their undergraduate classrooms. Prior research shows that teacher beliefs are robust and hard to change. Thus, the challenge is finding optimal avenues to influence these beliefs to help address the national call for engineering education reform.

Appendix A: Problems

Honey Bee Nest Thermoregulation: Diversity Promotes Stability

Julia C. Jones,[1]* Mary R. Myerscough,[2] Sonia Graham,[2] Benjamin P. Oldroyd[1]

A honey bee colony is characterized by high genetic diversity among its workers, generated by high levels of multiple mating by its queen. Few clear benefits of this genetic diversity are known. Here we show that brood nest temperatures in genetically diverse colonies (i.e., those sired by several males) tend to be more stable than in genetically uniform ones (i.e., those sired by one male). One reason this increased stability arises is because genetically determined diversity in workers' temperature response thresholds modulates the hive-ventilating behavior of individual workers, preventing excessive colony-level responses to temperature fluctuations.

Honey bee colonies need to maintain their brood nest temperature between 32°C and 36°C, and optimally at 35°C, so that the brood develops normally (19). Workers regulate temperature by fanning hot air out of the nest when the temperature is perceived as being too high and clustering together and generating metabolic heat when the temperature is perceived to be too low (19-21). Clearly, a graded rather than precipitous response is required, so that the colony does not constantly oscillate between heating and cooling responses. Does genetic variation among patrilines help colonies to produce an appropriate, graded response to temperature changes?

The preceding article from Science (*Science*, **305**, 16 July, 2004, 402-404) describes how heat transfer plays a key role in the biological function of a bee hive, and how the bees affect this process by regulating the temperature by flapping their wings or huddling together.

The bees' ability to maintain the optimal brood nest temperature of around 35 ºC is especially interesting to consider when there are fluctuations in the surrounding environmental temperature. In some honey bee environments the ambient temperature can fluctuate between 15ºC and 40ºC over a period as small as two days, putting a great thermal load on the hive. It has been shown that different genetic lines of bees have varying capacities for fanning action with their wings and may also have varying thresholds for turning on and off the fanning activity to change local hive temperature.

Nearly all of the research in this area has focused on analysis of bee behavior and its determinants. However, there is potentially useful information to be learned about how the thermal properties of a hive and the mechanisms of energy transport within it can influence the ability of bees to function in transient environmental conditions. Therefore, please think about and explain how you would quantify transient hive temperature to ultimately determine whether or not genetic diversity among bees helps stabilize hive temperature.

Your job is to determine an approach to analyzing and modeling the process by which bees are able to regulate the temperature of their hive.

Problem 2

The hot combustion gases of a furnace are separated from the ambient air and its surroundings, which are at 25°C, by a brick wall 0.15 cm thick. The brick has a thermal conductivity of 1.2 W/m•K and a surface emissivity of 0.8. Under steady state conditions an outer surface temperature of 100°C is measured. Free convection heat transfer to the air adjoining the surface is characterized by a convection coefficient of $h = 20$ W/ m^2•K. The Stefan-Boltzmann constant is 5.67×10^{-8} W/ m^2•K^4. What is the brick inner surface temperature?

Appendix B: Interview Protocol

Biotransport Interviews, Dissertation Pilot –Boulder October 2007
Think Aloud and Retrospective Report Protocol

• In this experiment we are interested in what you think about when you find solutions to biotransport problems.
• So, I am going to ask you to think aloud as you work on a problem.
• What I mean by think aloud is that I want you to verbalize everything you are thinking from the time you first see the question until you give an answer.
• Try to talk aloud constantly, explaining what you're thinking about while working on the problem. You can say anything that is on your mind such as, "Well at this point I'm going to . . . " or "Now I'm drawing such and such."
• Pretend that you are taking an exam. If you get stuck, try to unravel the problem on your own, and try not to ask me questions. Just act as if you are alone in the room speaking to yourself.
• It is important that you keep talking. Talking aloud may not seem natural, and you may feel strange doing it. That is a normal reaction, just try to continue talking.
• If you are silent for a long period of time I will remind you to talk.
• Verbalizing how you solve a problem takes more time than just solving the problem.
• Don't worry if it seems you are taking a long time.
• This is not an evaluation of you, and we are not concerned with whether you get a right answer.
• Instead, we are interested in how you think about complex problems.
• Now I'll demonstrate with an example and then we'll begin with some practice problems.

Think Aloud Examples

<u>*Simple Example*</u>
I'll talk aloud while solving an addition problem to give you an example.
(GET PAPER) 34 + 27

So, I have to add the 4 and the 7 and I get 11. so, I put a 1 down here and a 1 up here because this is the ones column and this is the tens column. Then I'll add the tens column. 1 + 3 + 2 = 6, so I'll write six down here and the answer is 61.

Warm-up Exercise

First, I want you to add these two numbers on paper and tell me what you are thinking as you get an answer. What is the result of adding 381 and 728?

Give student a hard copy of the addition problem with a pencil to work it out (see back pages of protocol).

Retrospective Instructions

• Good, now I want to see you much you can remember about what you were thinking from the time you read the question until you gave the answer.
• I'm interested in what you actually remember rather than what you think you must have thought.
• If possible I would like you to tell about your memories in the sequence in which they occurred while working on the problem.
• Please tell me if you are uncertain about any of your memories.
• I don't want you to work on solving the problem again, just report all that you can remember thinking about when answering the question.

• Now tell me what you remember.
THEY KEEP PAPER

******START TAPE, SAY NAME AND DATE**

Biotransport Problem

• Good. Now I will give a biotransport problem to solve.
• I want you to do the same thing for this problem as you did on the previous one.
• Think aloud as solve the problem.
• After you answer it I will ask you to tell me all that you can remember about your thinking.
• Do you have any questions?
• Here is the problem (problem is also at the end of the protocol).

The Bee Hive Problem

Honey Bee Nest Thermoregulation: Diversity Promotes Stability

Julia C. Jones,[1*] Mary R. Myerscough,[2] Sonia Graham,[2] Benjamin P. Oldroyd[1]

A honey bee colony is characterized by high genetic diversity among its workers, generated by high levels of multiple mating by its queen. Few clear benefits of this genetic diversity are known. Here we show that brood nest temperatures in genetically diverse colonies (i.e., those sired by several males) tend to be more stable than in genetically uniform ones (i.e., those sired by one male). One reason this increased stability arises is because genetically determined diversity in workers' temperature response thresholds modulates the hive-ventilating behavior of individual workers, preventing excessive colony-level responses to temperature fluctuations.

Honey bee colonies need to maintain their brood nest temperature between 32°C and 36°C, and optimally at 35°C, so that the brood develops normally (19). Workers regulate temperature by fanning hot air out of the nest when the temperature is perceived as being too high and clustering together and generating metabolic heat when the temperature is perceived to be too low (19-21). Clearly, a graded rather than precipitous response is required, so that the colony does not constantly oscillate between heating and cooling responses. Does genetic variation among patrilines help colonies to produce an appropriate, graded response to temperature changes?

The preceding article from Science (*Science*, **305**, 16 July, 2004, 402-404) describes how heat transfer plays a key role in the biological function of a bee hive, and how the bees affect this process by regulating the temperature by flapping their wings or huddling together.

The bees' ability to maintain the optimal brood nest temperature of around 35 ºC is especially interesting to consider when there are fluctuations in the surrounding environmental temperature. In some honey bee environments the ambient temperature can fluctuate between 15ºC and 40ºC over a period as small as two days, putting a great thermal load on the hive. It has been shown that different genetic lines of bees have varying capacities for fanning action with their wings and may also have varying thresholds for turning on and off the fanning activity to change local hive temperature.

Nearly all of the research in this area has focused on analysis of bee behavior and its determinants. However, there is potentially useful information to be learned about how the thermal properties of a hive and the mechanisms of energy transport within it can influence the ability of bees to function in transient environmental conditions. Therefore, please think about and explain how you would quantify transient hive temperature to ultimately determine whether or not genetic diversity among bees helps stabilize hive temperature.

Your job is to determine an approach to analyzing and modeling the process by which bees are able to regulate the temperature of their hive.

Retrospective Report

Now tell me all that you can remember about your thinking.

THEY KEEP PAPER

Problem 2

The hot combustion gases of a furnace are separated from the ambient air and its surroundings, which are at 25□C, by a brick wall 0.15 cm thick. The brick has a thermal conductivity of 1.2 W/m•K and a surface emissivity of 0.8. Under steady state conditions an outer surface temperature of 100□C is measured. Free convection heat transfer to the air adjoining the surface is characterized by a convection coefficient of h = 20 W/ m^2•K. The Stefan-Boltzmann constant is 5.67 x 10^{-8} W/ m^2•K^4. What is the brick inner surface temperature?

Retrospective Report

Now tell me all that you can remember about your thinking.

THEY KEEP PAPER

Potential questions/prompts

Think Aloud
Keep talking.
What are you thinking right now?
So now you are . . .
What are you doing now?
Why did you do that?
Describe the steps you are going through.
So this is . . .
Is there anything special you're looking for?

Retrospective

What was your goal?
What did you expect when you did that?
Repeat their own words/phrases back to them as a question. For example, "So that's confusing?"
Can you tell me what you were thinking?
What did you want to accomplish here?
How did you feel about that process?
Can you tell me why you did X?
You seemed surprised/puzzled/frustrated, were you?

TA and Retrospective Report adapted from *Protocol Analysis* (Ericsson & Simon, 1984) and "Methods for successful 'Thinking-Out-Loud' procedures" developed by Judy Ramey, Univ. of Washington, with additions by Usability Analysis & Design, Xerox Corporation (Pieratti, 1995).

References

Alberdi, E., Sleeman, D. H., & Korpi, M. (2000). Accommodating Surprise in Taxonomic Tasks: The Role of Expertise. *Cognitive Science: A Multidisciplinary Journal, 24*(1), 53-91.

Augustine, N. (2005). *Rising above the Gathering Storm: Energizing and Employing America for a Brighter Economic Future*. Washington, DC: National Academy of Science, National Academy of Engineering, Institute of Medicine, National Academy Press.

Binet, A. (1893/1966). Mnemonic virtuosity: A study of chess players. *Genetic Psychology Monographs, 74*, 127-164.

Carlson, M. P., & Bloom, I. (2005). The cyclic nature of problem solving: an emergent multidimensional problem-solving framework. *Educational Studies in Mathematics, 58*, 45-75.

Chase, W., & Simon, H. (1973). Perception in Chess. *Cognitive Psychology, 4*, 55-61.

Chi, M. T. H. (2005). Commonsense Conceptions of Emergent Processes: Why Some Misconceptions Are Robust. [Article]. *Journal of the Learning Sciences, 14*(2), 161-199.

Chi, M. T. H. (2006). Laboratory methods for assessing experts' and novices' knowledge. In K. A. Ericsson, N. Charness, P. J. Feltovich & R. R. Hoffman (Eds.), *The Cambridge Handbook of Expertise and Expert Performance* (pp. 167-184). New York: Cambridge University Press.

Chi, M. T. H., Feltovich, P., & Glaser, R. (1981). Categorization and representation of physics problems by experts and novices. *Cognitive Science, 5*(2), 121-152.

Clough, G. (2004). *The engineer of 2020: Visions for engineering in the new century*. Washington , DC: National Academy of Engineering, National Academy Press.

Clough, G. (2005). *Educating the Engineer of 2020: Adapting Engineering Education to the New Century*. Washington , DC: National Academy of Engineering, National Academy Press.

Crawford, V. M., Schlager, M., Toyama, Y., Riel, M., & Vahey, P. (2005). *Report on a laboratory study of teacher reasoning: Characterizing adaptive expertise in science teaching.* Paper presented at the American Educational Researchers Association Annual Conference, Montreal, Canada.

Diller, K.R. (2006) The Beehive Problem, Unpublished Course Materials.

de Groot, A. (1965). *Thought and choice in chess*.

Ericsson, K. A. (2006a). The influence of experience and deliberate practice on the development of superior expert performance. In K. A. Ericsson, N. Charness, P. J. Feltovich & R. R. Hoffman (Eds.), *The Cambridge Handbook of Expertise and Expert Performance* (pp. 683-704). New York: Cambridge University Press.

Ericsson, K. A. (2006b). Protocol analysis and expert thought: Concurrent verbalization of thinking during experts' performance on representative tasks. In K. A. Ericsson, N. Charness, P. J. Feltovich & R. R. Hoffman (Eds.), *The Cambridge Handbook of Expertise and Expert Performance* (pp. 243). New York: Cambridge University Press.

Ericsson, K. A., & Simon, H. A. (1984). *Protocol Analysis: Verbal Reports as Data*. Cambridge, MA: MIT Press.
Ericsson, K. A., & Simon, H. A. (1993). *Protocol analysis: Verbal reports as data*. Cambridge, MA: MIT Press.
Feltovich, P., Spiro, R. J., & Coulson, R. L. (1997). Issues of expert flexibility in contexts characterized by complexity and change. In P. Feltovich, K. M. Ford & R. R. Hoffman (Eds.), *Expertise in Context* (pp. 125-146). Menlo Park, CA: AAAI Press/MIT Press.
Gagne, R. M., & Smith, E. C. (1962). A study of the effects of verbalization on problem solving. *Journal of Experimental Psychology, 63*, 12-18.
Gobet, F., & Charness, N. (2006). Expertise in chess. In K. A. Ericsson, N. Charness, P. J. Feltovich & R. R. Hoffman (Eds.), *The Cambridge Handbook of Expertise and Expert Performance*. New York: Cambridge University Press.
Hatano, G., & Inagaki, K. (1986). Two courses of expertise. In H. Stevenson, J. Azuma & K. Hakuta (Eds.), *Child development and education in Japan* (pp. 262-272). New York, NY: W. H. Freeman & Co.
Hmelo-Silver, C. E., & Azevedo, R. (2006). Understanding Complex Systems: Some Core Challenges. [Article]. *Journal of the Learning Sciences, 15*(1), 53-61.
Hmelo-Silver, C. E., & Azevedo, R. (April 2006). *Understanding complex systems: Some core challenges.* Paper presented at the American Educational Research Association, San Francisco, CA.
Hmelo-Silver, C. E., & Pfeffer, M. G. (2004). Comparing expert and novice understanding of a complex system from the perspective of structures, behaviors, and functions. *Cognitive Science: A Multidisciplinary Journal, 28*(1), 127-138.
Hmelo, C. E., Holton, D. L., & Kolodner, J. L. (2000). Designing to Learn About Complex Systems. [Article]. *Journal of the Learning Sciences, 9*(3), 247-298.
Incropera, F. P., & DeWitt, D. P. (2002). *Fundamentals of heat and mass transfer*: John Wiley & Sons.
Jacobson, M. J., & Wilensky, U. (2006). Complex Systems in Education: Scientific and Educational Importance and Implications for the Learning Sciences. [Article]. *Journal of the Learning Sciences, 15*(1), 11-34.
Jonassen, D., Strobel, J., & Lee, C. (2006). Everyday problem solving in engineering: Lessons for engineering educators. *Journal of Engineering Education, 95*(2), 139.
Jones, J. C., Myercough, M. R., Graham, S., & Oldroyd, B. P. (2004). Honey bee nest thermoregulation: Diversity promotes stability. *Science, 16 July*, 402-404.
Korpi, M. (1988). *Making conceptual connections: An investigation of cognitive strategies and heuristics for inductive categorization of natural systems.* Unpublished Dissertation, Stanford University.
Lajoie, S. (2003). Transitions and trajectories for studies of expertise. *Educational Researcher, 32*(8), 21-25.
Larkin, J., McDermott, J., Simon, D. P., & Simon, H. A. (1980). Expert and novice performance in solving physics problems. *Science, 208*(4450), 1335-1342.
Lesgold, A. M., Rubinson, H., Feltovich, P., Glaser, R., Klopfer, D., & Wang, Y. (1988). Expertise in a complex skill: Diagnosing x-ray pictures. In M. T. H. Chi, R.

Glaser & M. J. Farr (Eds.), *The nature of expertise* (pp. 311-342). Hillsdale, NJ: Erlbaum.
Martin, T., Petrosino, A., Rivale, S., & Diller, K. R. (2006a). The development of adaptive expertise in biotransport. *New Directions in Teaching and Learning, Manuscript in press*.
Martin, T., Petrosino, A., Rivale, S., & Diller, K. R. (2006b). The development of adaptive expertise in biotransport. *New Directions in Teaching and Learning, Manuscript in press, 2006*(108), 35-47.
Martin, T., Petrosino, A., Rivale, S., & Diller, K. R. (2007). The development of adaptive expertise in biotransport. *New Directions in Teaching and Learning, Manuscript in press*.
Martin, T., Pierson, J., Rivale, S., & Diller, K. R. (in press). The role of Generating Ideas in challenge-based instruction. *iNEER Innovations, submitted.*
Martin, T., Rayne, K., Kemp, N. J., & Diller, K. R. (2005). Teaching for adaptive expertise in biomedical engineering ethics. *Science and Engineering Ethics, 11*(2), 257-276.
Martin, T., Rivale, S., & Diller, K. R. (2007). Comparison of student learning for challenge based and traditional instruction in Biomedical Engineering. *Annals of Biomedical Engineering, 35*(8), 1312-1323.
Martin, T., Rivale, S., & Diller, K. R. (in press). Comparison of student learning for challenge based and traditional instruction in Biomedical Engineering. *Annals of Biomedical Engineering*.
Nisbett, R. E., & Wilson, T. D. (1977). Telling more than we know: Verbal reports on mental processes. *Psychological Review, 1977*(84), 231-259.
Pandy, M. G., Petrosino, A., Austin, B. A., & Barr, R. A. (2004). Assessing adaptive expertise in undergraduate biomechanics. *Journal of Engineering Education, 93*(3), 1-12.
Raufaste, E., Eyrolle, H., & Marine, C. (1998). Pertinence generation in radiological diagnosis: Spreading activation and the nature of expertise. *Cognitive Science, 22*(4), 517-548.
Rayne, K., Martin, T., Brophy, S., & Diller, K. R. (2006). A cross-sectional examination of the development of adaptive expertise in bioengineering ethics. *Journal of Engineering Education, 95*(2), 165-173.
Resnick, M., & Wilensky, U. (1998). Diving Into Complexity: Developing Probabilistic Decentralized Thinking Through Role-Playing Activities. [Article]. *Journal of the Learning Sciences, 7*(2), 153.
Rivale, S., Martin, T., & Diller, K. R. (2006, July 23, 2006). *Gender differences in adaptive expertise: evaluation of a challenge based HPL biomedical engineering curriculum.* Paper presented at the International Conference on Engineering Education, San Juan, Puerto Rico.
Roselli, R. J., & Brophy, S. (2006). Effectiveness of Challenge-Based Instruction in Biomechanics. *Journal of Engineering Education*, 311-324.
Saariluoma, P., & Kalakoski, V. (1997). Skilled Imagery and Long-Term Working Memory. *The American Journal of Psychology, 110*(2), 177-201.

Schraagen, J. M. (1993). How experts solve a novel problem in experimental design. *Cognitive Science, 17*, 285-309.
Schunn, C. D., & Anderson, J. R. (1999). The generality/specificity of expertise in scientific reasoning. *Cognitive Science, 23*(3), 337-370.
Schwartz, D. L., Bransford, J. D., & Sears, D. (2005). Innovation and efficiency in learning and transfer. In J. Mestre (Ed.), *Transfer of learning from a modern multidisciplinary perspective* (pp. 1-51). Mahwah, NJ: Erlbaum.
Shulman, L. S. (1986). Those who understand: Knowledge growth in teaching. *Educational Researcher, February*.
Stanic, G., & Kilpatrick, J. (1988). Historical perspectives on problem solving in the mathematics curriculum. *Teaching and learning mathematical problem solving: Multiple research perspectives. Reston VA: NCTM*, 1-22.
Strauss, A., & Corbin, J. (1998). *Basics of Qualitative Research*. Thousand Oaks, CA: Sage Publications.
Voss, J. F., Tyler, S. W., & Yengo, L. A. (1983). Individual differences in the solving of social science problems. In R. F. Dillion & R. R. Schmeck (Eds.), *Individual differences in cognition* (Vol. 1). New York: Academic.
Wilensky, U., & Reisman, K. (2006). Thinking Like a Wolf, a Sheep, or a Firefly: Learning Biology Through Constructing and Testing Computational Theories—An Embodied Modeling Approach. *Cognition and Instruction, 24*(2), 171-209.
Wilensky, U., & Resnick, M. (1999). Thinking in Levels: A Dynamic Systems Approach to Making Sense of the World. *Journal of Science Education and Technology, 8*(1), 3-19.
Wineburg, S. (1997). Reading Abraham Lincoln: An expert/expert study in the interpretation of historical texts. *Cognitive Science, 22*(3), 319-346.

Vita

Stephanie Rivale is currently employed as the BOLD Center Director of K-12 Engineering Education in the College of Engineering and Applied Science at the University of Colorado at Boulder. In this position, she is focused on building the pipeline capacity and helping to create multiple pathways into engineering in addition to continuing research in Engineering Education. She received her BS in Chemical Engineering at the University of Rochester and her MS in Chemical Engineering at the University of Colorado. She has collaborated on engineering education research with both the VaNTH Engineering Research Center and *UTeachEngineering*. Stephanie's research uses recent advances in our understanding of how people learn to evaluate and improve student learning in college and K-12 engineering classrooms. Her work has also focused on improving access and equity for women and students of color in the STEM fields.

Permanent address (or email): stephanie.rivale@gmail.com

This dissertation was typed by Stephanie Rivale.