INVESTIGATING TRAJECTORIES OF LEARNING & TRANSFER OF PROBLEM SOLVING EXPERTISE FROM MATHEMATICS TO PHYSICS TO ENGINEERING

Problem solving strategies form the basic toolbox of scientists and engineers. These strategies are learned throughout science and engineering education. Early in the university career of future scientists and engineers, they primarily solve problems which are structured to demonstrate a particular concept or strategy. As their education advances these students are presented problems that are less structured and require diverse skills to reach a solution. Finally, in their jobs the former students will be faced with problems that may not have a solution or may require creative methods to solve. Thus, over the course of just a few years students must move from solving rather routine problems with well established methods that provide known solutions to tackling ill-structured, real-world problems.

The problem solving skills of STEM students clearly develop and change during their education. However, this education is not necessarily a well coordinated effort in which the complexity and type of problem changes in an orderly fashion. We know that introductory STEM courses present the students with textbook problems and that senior research projects are generally rather open-ended. However, we know little about how students progress from struggling with a calculation of a force using Newton's Second Law to creatively designing an improved switch to activate an airbag. Without such knowledge it is difficult to establish new procedures for the learning and teaching of problem solving skills.

This project is a step in creating a knowledge base on the evolution of students' problem solving skills. With the limited scope of a three-year project we cannot investigate student problem solving characteristics and changes through an entire academic career. However, we can build a foundation by looking at the development of these skills over several related academic courses. Thus, we will conduct

- 1. *Longitudinal* studies following a cohort group of students across multiple courses in mathematics, physics and engineering to compare the development and transfer of problem solving expertise in individual students.
- 2. *Cross-sectional* studies that take a 'snapshot' of student problem solving in several courses to compare the development and transfer of problem solving expertise across various courses.

A combination of qualitative and quantitative methods will provide a new look at how students develop and transfer their problem solving expertise. The project will also suggest ways in which we can improve the development and transfer of problem solving expertise.

Goals & Overview of Project

Significant research on problem solving in STEM disciplines has discovered a variety of factors influencing students' problem solving performance. In spite of these efforts many issues remain worthy of further investigation. We have identified four research questions (RQs) for our project:

- <u>RQ 1.</u> How does students' expertise to solve problems of increasing complexity evolve over time? How can we enable learners to solve problems of increasing complexity?
- <u>RQ 2.</u> In what ways does representational form, organization and sequencing affect students' problem solving expertise? How can we facilitate learners' development of representational competence?
- <u>RQ 3.</u> How does the trajectory of acquiring problem solving expertise vary with context and domain? How can we facilitate transfer of problem solving expertise across contexts and domains?
- <u>RQ 4.</u> What are the differences between the trajectories of students' acquiring problem solving expertise? How do these trajectories change over time? Can students be classified based on their trajectories? How can we individualize learning tools to adapt to different students?

Each of the aforementioned research questions will be explored over two phases of research in:

(a) *Phase I: Out-of class* studies: Utilizing primarily qualitative methods such as learning/teaching interviews we will conduct a fine-grained analysis of individual student's problem solving to address the above questions.

(b) *Phase II: In-class* studies: Based on insights from (a), we will enhance an existing online homework tutoring system and implement it in all of the targeted courses. Data mining and quantitative methods will be used to address the above questions.

The participants in our studies will be enrolled in various math, physics and engineering courses (see Work Plan later in proposal). We will follow a cohort group of students *longitudinally* as they move through this sequence of courses. We will also look at semester long *cross-sectional* snapshots of all courses with different sets of students. Over 3000 students will participate in research conducted over the duration of this project.

Literature Review

Problem Solving

Following Jonassen (2007), we assume that problem solving varies along three dimensions: problem features, problem representation and individual differences between problem solvers.

Problem features are based on *structuredness* (well-structured vs. ill-structured), *complexity* (simple vs. complex), *domain specificity* (abstract vs. situated) and *dynamicity* (static vs. dynamic).

The *structuredness* of a problem describes the nature of both the solution and the way to arrive at that solution. Well-structured problems have well defined initial states (what is given) and well defined final states (what is asked for) as well as a well defined path to reach the solution. At the other end of the continuum are ill-structured problems. They do not have well defined initial or final states and may require knowledge from a vast array of content domains. They frequently can be (or must be) solved by multiple strategies and approaches, all of which require trade offs and compromises of some kind. These problems are similar to those encountered in everyday life, while typical end-of-chapter problems in university-level science and math courses are well defined. In this project we focus primarily on well-structured problems, similar to those found at the end of the chapter in most texts.

Complexity refers to the number of different kinds of concepts and pieces of information that the problem solver has to juggle and how these concepts interact with each other. The complexity is a measure of the memory load that is required to solve the problem. In this project we study how students learn to solve increasingly complex problems as well as the hints, cues and other scaffolding that different learners need to solve problems of varying complexity.

Domain specificity refers to the *context* in which the problem is stated. Highly abstract problems, similar to those frequently encountered in a mathematics course, have no connection to the real world. Other problems are deeply embedded in real-world contexts, for example engineering design projects. In this project we will study how *context* affects the ways in which students learn to solve problems. We will also learn how students transfer their problem solving skills from mathematics to physics to engineering.

Dynamicity refers to the extent to which the problem parameters change over time. A static problem is one in which the parameters are stated and never vary while a highly dynamic problem involves variables which frequently change with time. While real-world problems are frequently dynamic, problems posed for learning in a classroom are mostly static. Therefore, we focus on static problems.

Problem representations are characterized based on the *form*, *organization* and *sequencing* of the problem information.

The *form* of a problem refers to the way in which the problem information is represented. For example, some problems may be presented in only textual form while others may include equations, graphics and perhaps even video. In this project we will examine how representational form affects students' ability to solve problems and to transfer learning during problem solving.

The *organization* of the problem refers to the use of structures such as tables, graphs, structure maps, etc. that help organize information. Graphs and tables, and less commonly concept maps, are used to present information in physics, math and engineering courses. We will study the impact of these

organizational structures on student learning. We have already completed research on the use of structure maps to gauge students' problem solving abilities and conceptual understanding. We have found that while some students find the concept map to be useful, they are unlikely to abandon their novice problem solving strategies or assimilate concept mapping into their problem solving repertoire unless they are explicitly required to do so. (Mateycik, Hrepic, Jonassen & Rebello, 2007) We will build on our work with concept maps and extend it to other organizational tools in this project.

The *sequencing* of the problem information refers to the order in which the information is provided. In our research we will study how the sequencing of the various parts of a problem and various representational forms affect students' problem solving expertise.

Individual differences that mediate the problem solving abilities of students include their domain knowledge, experience in solving problems, thinking and reasoning skills and their epistemological development. Domain knowledge has been recognized as being one of the most important characteristics especially with regard to well-structured problems (Greeno, 1980; Hayes, 1989; Rittle-Johnson & Alibali, 1999). We will use conceptual inventories such as FCI – Force Concept Inventory (Hestenes, Wells, & Swackhammer, 1992) to measure students' domain knowledge. Problem solving experience typically refers to real-world experiences that learners may have had that better prepare them to be problem solvers. There is little one can do to control such prior experience in a study such as ours. However, we will collect data on students' prior job related and real-world knowledge as well as classroom experience as we recruit participants in our study. The thinking and reasoning skills deemed most important for problem solving are analogical reasoning (Gentner, 1983) and causal reasoning (Keil, 1989). Both of these reasoning processes are central to our studies. We will examine both of them through our learning/teaching interviews. Finally, epistemic beliefs about knowledge and learning have long been deemed an important factor in students' problem solving abilities. Several theories (Perry, 1970) of how individuals develop epistemologically from a dualistic to relativistic perspective have been proposed. A more recent framework by Hammer and Elby (2002) on epistemological resources that a learner activates based on how he/she frames the situation might be most relevant in this study. We will ascertain learners' epistemology through our interviews as well as surveys such as EBAPS - Epistemological Beliefs Assessment for the Physical Sciences (Elby, 2001).

| Dimension | Attribute | Study? | What & how do we study? | | |
|-----------------------------|----------------------------|--------|---|--|--|
| Problem Features | Structurednesss | No | Well-structured only | | |
| | Complexity | Yes | Increasing number of concepts required | | |
| | Domain specificity | Yes | Changing contexts | | |
| | Dynamicity | No | Time independent problems <i>only</i> | | |
| Problem Re- presentation | Form | Yes | Text / Pictures / Graphs / Symbols | | |
| | Organization | Yes | Use of structure maps and other organization tools | | |
| | Sequencing | Yes | Vary order of the information or the sub-questions | | |
| Individual Differences | Domain knowledge | Yes | Interviews and conceptual inventories (e.g. FCI) | | |
| | Problem solving experience | Yes | Interviews to explore problem solving background | | |
| | Reasoning skills | Yes | Interviews to gauge analogical and causal reasoning | | |
| | Epistemological maturity | Yes | Interviews and surveys (e.g. EBAPS) | | |

Table 1 below summarizes the research discussed above and how it applies to our project

Table 1: Summary of problem solving literature and how it applies to our project

Transfer of Learning

Transfer of learning is often defined as applying knowledge and skills learned in one situation to another situation (Reed, 1993; Singley & Anderson, 1989). Typically, researchers have pre-defined what they hope students will transfer. They have viewed this as a static, passive process and focused mainly on the cognitive aspects of transfer. Lack of evidence of transfer in many studies based on traditional models has led researchers to consider other perspectives of transfer. Contemporary perspectives have gone beyond the cognitive aspects of transfer. The socio-cultural perspective asserts that the social and cultural environment affects transfer through language, cultural tools and interaction with people. Transfer is the

extent to which participating in an activity while being attuned to the affordances and constraints in one situation influences the learner's participation in a different situation (Greeno, Moore, & Smith, 1993). The actor-oriented perspective conceives transfer as the personal construction of similarities between activities where the 'actors,' i.e. learners, see situations as being similar (Lobato, 1996). Preparation for future learning focuses on whether students can *learn* to solve problems in transfer situations (Bransford & Schwartz, 1999). In all contemporary perspectives transfer is a dynamic process of reconstruction of knowledge in a new situation rather than merely applying previously learned knowledge intact to a new situation.

To measure transfer we must investigate when, how and why learners activate certain small grain resources, what contextual characteristics cue activation, how they coordinate these resources with new information and what factors control the coordination. These variables are similar to ones in a model proposed by Redish (2004). Further, we must investigate the extent to which this activation and coordination results in compilation of larger grain size knowledge structures such as coordination classes (diSessa, 1998; diSessa & Wagner, 2005) or mental models (Johnson-Laird, 1983) that are not overly contextualized and can be used appropriately in future contexts. Transfer is a complex, dynamic process that must be probed through *in vivo* techniques focusing on process over product (Rebello *et al.*, 2005).

Our model of transfer (Rebello, Cui, Bennett, Zollman, & Ozimek, 2007) incorporates two

qualitatively different processes. Vertical transfer is the activation of small grain resources from long term memory and their association or coordination to compile larger grain size knowledge structures that more stable. are Horizontal transfer is the application of developed compiled knowledge well structures to new contexts. Other researchers have made similar distinctions Salomon and Perkins (1989)e.g. contrasted 'low road' transfer and 'high road' transfer. Bransford and Schwartz (1999) discuss transfer in terms of 'sequestered problem solving' which horizontal promotes transfer while 'preparation for future learning' promotes diSessa and Wagner vertical transfer.



(2005) have applied coordination class theory (diSessa, 1998) to distinguish Class A transfer, i.e. applying well prepared knowledge and Class C transfer, i.e. constructing new knowledge. Similarly, Schwartz, Bransford and Sears (2005) discuss transfer in terms of efficiency and innovation.

To help students become both efficient and innovative problem solvers, i.e. develop adaptive expertise, Schwartz, Bransford and Sears (2005) posit that we must guide students through successive steps of innovation (vertical transfer) and efficiency (horizontal transfer), i.e. along an optimal adaptability corridor. These ideas of transfer also connect with theories of constructivism. As shown in Figure 1, the vertical step size is governed by the learners' zone of proximal development – the difference between what they can innovate by themselves and what they can innovate with scaffolding provided by a more experienced individual (Vygotsky, 1978). When one is no longer able to horizontally transfer existing knowledge to a problem situation and therefore needs to innovate is a point of cognitive dissonance or disequilibrium (Piaget, 1964). Each horizontal and vertical step is scaffolded by instruction via a process of metacognition and self-regulation by the learner who reflects on the process of learning. Thus, this model of transfer (Rebello, Cui, Bennett, Zollman, & Ozimek, 2007) consolidates both traditional and contemporary views of transfer and serves as a building block for the theoretical framework in this project.

Theoretical Framework

Our theoretical framework can be described on a three dimensional (3D) diagram in Figure 2. Not all the attributes of problem solving are studied. For instance, the effect of change in *structuredness* or *dynamicity* are not studied and therefore do not appear on the diagram below

z-axis: Vertical transfer (innovation) involves developing new knowledge for solving problems of increasing complexity. The *z*-axis in our diagram is the *complexity* attribute in Table 1.

y-axis: Horizontal transfer (efficiency) involves applying precreated knowledge to a new context. As problem solving expertise improves, students increase the number of domains for which they can successfully address problems. The y-axis in our 3D diagram is the *domain* attribute (Table 1) with the number of domains increasing as one goes from left to right along the axis

x-axis: Horizontal transfer (efficiency) also involves being able to apply your knowledge to problems in



different representations. The x-axis is the number of *representation* (Table 1) in which the student is competent.

The 3D representation allows us to describe an *individual learning trajectory* – a path toward expertise that involves developing the ability to solve increasingly *complex* problems, in a variety of *representations* and in different *domains*. In our research we investigate the kinds of scaffolding necessary to guide students toward expertise as defined in this 3D framework. The scaffolding needed as well as the level of complexity, domain specificity and representational competence achieved will vary with individual students. Therefore different students will follow different learning trajectories.

The research questions for this project align with the theoretical framework as follows.

- RQ 1 investigates the development of expertise to solve problems of increasing *complexity*.
- RQ 2 investigates the effect of problem representation on students' problem solving expertise.
- RQ 3 investigates the development of problem solving expertise across different domains.

RQ 4 investigates individual learning trajectories toward acquiring problem solving expertise.

Research Plan

Our research plan incorporates studies in both out-of-class experimental settings as well as real inclass learning environments. In-class environments involve many variables which are difficult to control, so we start with out-of-class studies and build to investigating in-class activities later.

Phase I: Out of Class Studies

We aim to understand student's individual learning trajectories and zones of proximal development as they move toward the development of problem solving expertise. We will conduct both longitudinal and cross-sectional studies across several students in different courses. Phase I in each kind of study will involve learning/teaching interviews.

Research Instrument – Learning/Teaching Interviews: The learning/teaching interview is an adaptation of the teaching experiment that has been used in mathematics (Steffe & Thompson, 2000) and physics education (Katu, Lunetta, & van den Berg, 1993). Our adaptation was developed by Engelhardt

Corpuz, Ozimek and Rebello (2003). We have since honed this methodology to be useful for *in vivo* investigations of students' learning and dynamic transfer (Corpuz & Rebello, 2006). In the learning/teaching interview the researcher is simultaneously the interviewer and a teacher. An independent observer is present to take field notes and intervene when necessary. The learning/teaching interview is a mock instructional setting for employing research-based scaffolding strategies discussed later. Thus, the learning/teaching interview is an adaptive methodology that helps investigate the dynamics of students' problem solving expertise and transfer.

Alignment with Theory: The learning/teaching interview creates an environment that offers a rich repertoire of experiences for the learners. It allows the researcher to modify the problem *representation* and *domain* or increase the *complexity* on the fly and probe how learners respond to these changes. It also provides an opportunity as to how the learner can respond to cues, hints and other scaffolding. Thus, the learning/teaching interview allows the researcher to probe an individual student's zone of proximal development (Vygotsky, 1978) and serves as a useful tool to investigate problem solving and transfer based on contemporary perspectives (Bransford & Schwartz, 1999; Lobato, 1996, 2003). Overall, the learning/teaching interview allows the researcher to probe all three dimensions of the framework: *complexity, representation* and *domain*, as well as investigate *individual differences* between learners.

Participant Selection: In each course targeted by this study we will interview 20 students six (6) times over the duration of the semester. Students will be offered \$10 per interview episode. Our experience indicates that this monetary incentive draws a large pool of volunteers to choose from. Particular attention will be paid to selecting students who will participate in the longitudinal studies. These volunteers will be informed that they will be participating in a multi-semester study across multiple courses. These volunteers will be screened based on their past record of completing courses so that we ensure that our pool does not dwindle as we proceed. In selecting our interview participants we will strive to balance students of different academic backgrounds, gender and ethnicity.

Data Collection: To observe how students develop their problem solving expertise over a semester we will complete six (6), 60-minute long learning/teaching interview episodes with each student. The first learning/teaching interview episode will be completed within the first 10 days of the semester. The main purpose of this episode will be for the teacher-researcher and the student to start to develop a rapport that will hopefully build throughout the semester. The first episode will also be used to collect information about the individual students' academic and real world background related to problem solving and allow them to air any concerns or questions the interviewee may have about the course or the research study. At the end of the first interview episode, the interviewee will also be asked to complete online conceptual surveys relevant to the topics covered in the course (e.g FCI for a first semester physics course) as well as surveys gauging their epistemology (e.g. EBAPS). Data from the first interview episode and surveys will be utilized to gauge the student in terms of her/his initial starting point in the course with regard to prior content knowledge, problem solving experience, expectations and epistemological maturity.

Our previous research (Allbaugh, 2003) has shown interviewing students a day or two after they have taken an hour exam in the course is most useful. Starting with the second episode, in each episode the interviewee will be presented with up to four 'think aloud' problem solving tasks that are based on content that students covered on the recently taken exam. In an ongoing project, we adapted a sequence of problem solving tasks used by Nokes (2007) that has enabled us to investigate how students solve different kinds of problems (Mateycik, Hrepic, Jonassen & Rebello, 2007).

The first problem in each learning/teaching interview episode will be similar to one they encountered in their homework assignment the previous week. The goal of the first problem is to activate the conceptual and epistemological resources that students typically use while solving problems.

The second problem will be identical to the first, except that it is *representationally different* from the first problem in terms of form, organization or sequencing of information that is either provided or required. The goal of the second problem is to investigate the extent to which learners can develop the representational competence (Ainsworth, 2006) to manipulate the information in different representations.

The third problem will be identical to the second problem except that it will be in a *different domain* from the second problem. The third problem is based on the same principle and utilizes the same representations as the second.

Finally, the fourth problem will be an extension of the third problem but it also calls for use of a new principle or concept in addition to those used in the first three problems. Thus the fourth problem requires a *higher complexity* than the first three problems, because the learner has to expand her/his conceptual schema to solve this problem.

Figure 3 shows a generic learning trajectory of an individual student. Each learning/teaching interview episode has



Figure 3: Problem sequences in each interview episode

four problems varying representation, domain and complexity. Figure 4 provides an example of the sequence of problems in the topical area of kinematics and dynamics in an introductory physics course.



For each of the four problems above, the student will first be presented with the problem and asked to think aloud as they work their way through the problem. If the student is unable to proceed at any point, the teacher-researcher in the learning/teaching interview will provide appropriate scaffolding to assist the student in solving the problem.

Several scaffolding strategies have been suggested in literature that the teacher-researcher will explore during the learning/teaching interview episode. Some of them are described below:

- 1) Questioning The questioning strategy suggested by Graesser, Baggett and Williams (1996) poses a series of questions, such as "What principle do you think is involved here?" and "What are the quantities that are required/given in the problem?"
- 2) Case Reuse: Another scaffolding strategy refers the learner to a solved example that shares conceptual similarities with the given problem. This strategy is based on case reuse (Jonassen, 2006) which in turn is based on case-based reasoning (Kolodner, 1997).
- 3) Concept Mapping: Scaffolding can also be provided in the form of a conceptual structure or concept map (Nesbit & Adescope, 2006) that provides an organization scheme of the conceptual knowledge necessary to solve the problem. Based on our recently completed research (Mateycik, Hrepic, Jonassen, & Rebello, 2007) we have found that equations arranged in a coherent structure map provide learners with a conceptual and procedural schema that is useful for problem solving.
- 4) Providing Resources: Yet another scaffolding strategy is to provide students with the necessary conceptual or procedural resources by directing them to a passage in the text or a prepared video clip portion of the class where the relevant concepts or problems are discussed. One of the PIs (Bennett) has already implemented this strategy in his online system (discussed later).

In addition to utilizing the scaffolding strategies discussed above, for problems 2 through 4 in each episode, the student will also be asked to 'reflect aloud' about the similarities and differences between various problems as well as their solutions. At the end of each 60 minute learning/teaching interview episode the learner will be asked to write a 'minute-paper' reflecting on what they learned about problem solving during that learning/teaching interview episode and how it relates to previous learning/teaching interview episodes. Similarly, at the beginning of each learning/teaching interview the student will be asked to recall what they learned in the previous episode.

Overall, the teacher-researcher will explore the use of the above scaffolding and reflection strategies to enable the student to not just solve the problems, but also develop metacognitively and epistemologically with regard to problem solving. We do not anticipate that all students will be able to accomplish all four problems in a learning/teaching interview episode. Indeed, we anticipate that different students will require different levels and types of scaffolding during the learning/teaching interview and will also accomplish the problem solving tasks with different levels of success. Therefore the teacher-researcher may need to adapt and modify the problem tasks as well as the scaffolding strategies based on the individual differences between students.

The focus of the learning/teaching interview will be to understand the individual differences between learners. There are three aspects of *individual differences* that we will characterize in this study:

- <u>Internal characteristics</u>: This refers to students' conceptual knowledge and reasoning resources that they employ as well as their epistemological maturity with regard to problem solving. We will also examine degrees of success that students achieve as they navigate multiple representations, transfer their problem solving expertise to different contexts and solve increasingly complex problems.
- <u>External characteristics</u>: Another criterion used to distinguish between students is to measure the kinds scaffolding that they need to solve a problem. Different individuals, depending upon their past experiences, react differently to cues and hints to solve a problem
- <u>Zone of Proximal Development</u> (ZPD) has been defined as the difference between what the learner accomplishes by her/himself and what s/he achieves with assistance from a more knowledgeable peer (Vygotsky, 1978). By comparing the learners' ability to handle problems of increasing complexity, with and without scaffolding from the teacher-researcher, we will be able to estimate the ZPD of each individual learner. Thus the ZPD is based on both internal and external characteristics. In the next section we discuss ways in which the ZPD can be estimated based on interview data.

Thus our data collection and analysis approach from each learning/teaching interview episode will focus on getting a time 'snapshot' of each individual student's problem solving attributes as per the theoretical framework. These data will be integrated across all six (6) learning/teaching interview

episodes to map out the learning trajectory of each student across the entire course. In the *longitudinal* study, these individual students will be followed through different courses to develop a profile of how these individual students change across various courses in math, physics and engineering. In the *cross-sectional* study, each course will be studied with different students each time.

Data Analysis: Each learning/teaching interview episode will be audio/videotaped and transcribed. The transcript will be analyzed using a fine-grained, resource-based analysis. The analysis will focus on addressing the following questions about each student in the episode

- What *conceptual resources* did the learner activate while solving the problem? Under what conditions (e.g. with or without scaffolding) were these resources activated? To what extent were these resources organized into a schema, i.e. a set of interconnected resources that activate together?
- What were the *reasoning resources* that the learner employed as she/he attempted to solve the problems? To what extent did the learner utilize analogical encoding and causal reasoning while attempting the problems?
- What were the underlying *epistemological resources* that the learner appeared to employ while solving the problems? How did these resources affect the ways in which learners activated other (conceptual, procedural and reasoning) resources? How did these change with different problems?
- To what extent did the scaffolding provided to the learner help her/him solve problems across multiple representations, different contexts and increasing levels of complexity? How did the learner react to each type of scaffolding provided?

The teacher-researcher and observer will each code the data using the following layers of analysis as described below. An 80% inter-rater reliability and 90% intra-rater reliability will be met.

Phenomenographic Analysis (Marton, 1986) In this first layer of analysis, each phrase or sentence in the transcript will be coded based on the first three questions above, to ascertain the *conceptual resources*, *reasoning resources* and *epistemological resources* that the learner used. Examples from some of our past research include conceptual resources such as Newton's II Law (Allbaugh, 2003) or procedural resources such as 'searching for the right equation' (Mateycik, Hrepic, Jonassen, & Rebello, 2007). Coding for epistemological resources may or may not be possible in each case since ascertaining the epistemological mode in which the learner operates is sometimes difficult. Hammer and Elby (2002) have identified at least three resources in which learners operate – 'knowledge is fabricated,' 'knowledge from authority' and 'knowledge is freely created.'

The categories for coding each type of resource are not determined *a priori* but emerge from the analysis of the responses rather than researchers' preconceptions. After completing the analysis for each interviewee, we will compare individual students (Bogdan & Bilken, 1998).

- *Thematic Analysis* (Bogdan & Bilken, 1998) Themes are expected to emerge from various phenomenographic categories. The themes encapsulate the general trends across all students and help us make some generalizations about the ways in which students approached the problem solving tasks.
- *Interaction Analysis* We will adapt the methods used to assess one-on-one tutoring (Chi, 1996; Chi, Siler, Jeong, Yamaguchi, & Hausmann, 2001; Graesser, Person, & Magliano, 1995) to analyze the ways in which students interact with the teacher-researcher. These methods are particularly relevant while addressing RQ4 pertaining to the scaffolding provided by the teacher-researcher and how the learner reacted to each kind of scaffolding.
- *ZPD Analysis*: Based on the phenomenographic coding and interaction analysis we will attempt to map the Zone of Proximal Development (ZPD) for each student. While the ZPD has been cited as a useful theoretical construct, few attempts have been reported in literature to actually quantify the ZPD (Allal & Ducrey, 2000). An attempt to measure ZPD that is most relevant to this project was proposed by Murray & Arroyo (2002). In a study of solving online problems, the researchers measured the number of hints and correct responses to a sequence of problems that students were asked to solve. The ZPD was then calculated as a measure of the number of problems solved to the number of hints provided by the system. Clearly, our method of measuring ZPD needs to account for the type of scaffolding hints

as well as the level of complexity of the problems that the students can solve with these hints. We will devise a measure for ZPD based on the type of scaffolding provided by the teacher-researcher as well as the level of complexity of the problem solving task.

Addressing Validity Threats The following threats to validity confront this type of study.

- <u>Participant Sampling</u>: There is no way to ensure that our interview participants are representative of the class as a whole. However, we will keep track of students' scores on the exams so that we can know *post facto* how our interview participants compare with the rest of the class in terms of their performance on course assessments. This will be taken into account as we report on our findings.
- <u>Lack of Saturation</u>: Data from 20 participants may not capture all categories of resources. Research has shown that 12 participants are sufficient to achieve saturation (Guest, Bunce, & Johnson, 2006).
- <u>Scaffolding Bias</u>: Scaffolding might lead students toward problem solutions without affording them the opportunity to figure it out for themselves. Teacher-researchers will be appropriately trained to provide the right kinds of cues and hints without leading the student along. Each interviewer will also conduct a few trial interviews as they hone their learning/teaching interview skills.
- <u>Student Improvement</u>: By continually reflecting on their problem solving skills the learning/teaching interviews help students become better problem solvers. Thus, it is likely that over time our longitudinal cohort become better problem solvers than their peers who are not involved in the study. So we also conduct cross-sectional studies in the targeted courses with students that are not a part of the longitudinal cohort group and have not learned through the interviews.

Expected Outcomes: Out-of-class learning/teaching interview studies will be completed in each relevant course of the project. In each course, the goal is to map the learning trajectory of individual students. The learning trajectory will contain information pertaining to the following:

- What are the *conceptual*, *reasoning* and *epistemological resources* that the learner activates while solving problems?
- How do these resources change when varying the *problem representation* and *domain* as well as level of *complexity* of the problem?
- How does the learner respond to different kinds of *scaffolding* as they solve different problems? Based on this information, to what extent can we estimate the *ZPD* of individual learners?
- How do the answers to the above questions *change with time* over the semester as the learner progresses through the course across multiple courses in the longitudinal study?

Another important outcome of this study will be the emergent themes and variations in learning trajectories. The outcomes of this phase will inform studies in in-class learning environments.

Phase II: In-Class Studies

The out-of-class studies map individual learning trajectories in a given course and across multiple courses. However, it is important to extend these studies to investigate how entire populations taking these courses learn to develop problem solving expertise. To accomplish this task we use online-learning environments that are deployed in the targeted courses.

Research Instrument – Online System: Since 2001 one of the co-PIs (Bennett) has developed, tested and used an online system to collect research data in trigonometry, calculus and algebra. The system has also been adapted by another co-PI (Warren) in a Linear Systems course required for all electrical and computer engineering undergraduates. Several features of this system make it both an excellent online tutoring system and research tool. The system randomly generates problems of similar types but with different numbers and, when appropriate, different contexts for word problems. While the problems are of similar types in statement (e.g. integrate the following function) the solution techniques will often differ depending on the particular functions used, e.g. whether a trig substitution or partial fractions is the appropriate tool. Students can enter answers in a variety of formats depending on the specific problem, including not just multiple choice and numerical values but also formulas and graphs. Each student gets an individualized problem set and their work can be saved for later - they do not have to enter answers in

the session where the problems are posed (though of course that is possible). When appropriate, answers are checked for syntactical correctness before grading, so obvious typos, e.g. mismatched parentheses can be identified and corrected without penalty. Answers are graded automatically, even the graphs and problems with multiple correct answers, e.g. indefinite integrals in which the arbitrary constant can lead to many different forms of the answer. After the first submission of their work, the system marks answers as correct or incorrect, and students are given a chance to fix their errors. After the second submission, they are then told what the correct answer is for any problem they still have wrong, and are given a link to a help screen that will show them in detail how to work that specific problem. We have recently experimented with including a link to a videotape segment of the class during which the instructor discusses that type of problem. At this point the students can request a second problem set and beyond. This generates another set of similar problems with differing functions and other details. Students receive their highest score over all their attempts. On average students attempt between two and thee problem sets for each assignment.

This system has advantages from both an educational and an assessment standpoint. Students have given positive reviews to this system with particular praise for the flexibility of the parser in accepting different types of answers and for the extensive help available so that it is a learning system as well as a research tool. Giving the students a chance to correct wrong answers gives practice in finding and fixing errors and also limits complaints about answers being marked wrong because of data-entry errors. In addition to the instructional advantages, getting significant feedback after the second attempt leads students to focus on those specific problems. When students know they will likely work another problem set or two containing different problems, they focus more on learning the general techniques, i.e. developing their conceptual and procedural resources. Limiting the number of attempts on a single problem set also means students must work to get the problems right, rather than use a trial and error approach of submitting multiple solutions.

From a research perspective multiple online problems will provide us with significant data on the evolution of students' problem solving and gives us a chance to try to measure learning of problem solving while it is happening in a real class, rather than just assessing it in an artificial interview. Finally, online data-mining lets us obtain data on much larger numbers of students than can be interviewed, enabling us to corroborate and extend the ideas developed from our out-of-class research.

Alignment with Theory: Our hypothesis is that learning accelerates when students gain a conceptual understanding. As per our theoretical framework, this hypothesis is consistent with a learning trajectory characterized by an increasing slope in Figure 3. We will use cluster analysis both to identify different student learning strategies and to develop tools for measuring when correlations between different classes are caused by transfer of learning.

Data Collection: The system automatically tracks all aspects of the students' interactions with the system. In particular, the system records when the student logs in to the system and from what IP address, when they look at problems or save any work, what problems they receive and what answers they give, whether those answers are correct, what changes they make after the first submission, whether they looked at the help screen and, if available, if they reviewed the videotape of classes during which that material was covered. Since the system was developed locally, we are able to add tracking for any additional aspects we may find desirable. For example, students submit graphs by creating them in an applet, which generates a computer-readable format that can be graded. We have experimented with tracking how the students interact with the applet to try to follow the steps they go through in solving the problem and getting a graph in correct form. In addition, we can look at how domain changes (sometimes as simple as changing a kinematics problem from a ball to a car – see Figure 4) change the difficulty of a problem by cuing different approaches. All information is stored in a SQL database where it can then be analyzed using data-mining techniques. For selected sections, we also store grades on traditional written assignments and problem by problem scores on in-class exams and the final to correlate with online data.

Data Analysis: We will use cluster analysis both to identify different student learning strategies and to develop tools for measuring when correlations between different classes are caused by actual transfer of

learning. Developing appropriate statistics and models that predict aspects of student learning and transfer will be a major part of our research effort. The phenomenographic analysis of Phase I will provide the starting categories for the data mining in this phase.

With data mining we can look at students' problem solving characteristics across domains and representations as the complexity of the problems increase. A student who is able to solve problems in different domains and in different contexts will move along a trajectory that leads to expertise in problem solving. These students can be identified through the data. Then we look at how these students solved the problems and what common characteristics they have or what common scaffoldings they required.

Expected Outcomes: The online system will collect data on over 75,000 problems from over 600 students each semester. We will analyze these data to develop models of learning and transfer with reasonable confidence levels which can address the following questions:

- What strategies (defined at least in part via available *resources*) do students pursue in learning and how do these affect their success?
- How do *domain* changes which cue different strategies change the difficulty of a problem?
- What percentage of students (and ideally, can we identify them individually) are ready to *transfer* their knowledge to new situations either in the same class or in later classes?
- How do these models (and ideally, individual student behaviors) *change with time*, comparing models for introductory classes to those for more advanced classes?
- For all of the above questions, what strategies and characteristics are common to those students who follow trajectories toward expertise in problem solving?

Work Plan

We will conduct two kinds of studies - Cross-Sectional and Longitudinal

- *Cross-Sectional:* Problem solving in each target course will be investigated with a different group of students to capture a snapshot of student learning multiple times during the project.
- *Longitudinal*: A cohort of 20 students will be followed through a sequence of courses (see timeline). We will complete one cross-sectional snapshot in each course before beginning the longitudinal study in each course.

Each study will have two phases

- *Phase I: Out-of-Class* provides results on individual learning trajectories of problem solving, which are fed into the next phase. *Phase I* is shown in green in the timeline below.
- *Phase II:* Utilized data on individual learning in Phase I, to inform the development of the online system used in real courses. *Phase II* is shown in pink in the timeline below.

| Phase | Goal | Research Instrument | Expected Outcomes |
|--------------|----------------------|----------------------------|---|
| Phase I: | Investigate | Individual | Variations in individual learning trajectories and |
| Out-of-Class | individual students' | learning/teaching | emergent themes regarding development and |
| | learning trajectory | interviews with a cohort | transfer problem solving expertise that can be |
| | and ZPD in | group of 20 students, 6 | used to design the online system used in Phase II. |
| | problem solving | times each semester. | |
| Phase II: | Investigate | Online homework | Models for student learning that permit |
| In-Class | problem solving in | administered weekly | measurements of typical problem solving |
| | a real learning | throughout the semester | expertise in a class along with predictions for the |
| | environment | to all students in the | percentage who will be able to transfer this to |
| | | targeted courses. | later classes |

In each course, the data are analyzed from one study and inform the next study as indicated below.

| | Longitudinal Phase I study | |
|-------------------------------|--------------------------------|-----------------------------|
| Cross-Sectional Phase I study | | Longitudinal Phase II study |
| | Cross-Sectional Phase II study | |

| Task | | 2008 | 2009 | | | 2010 | | | 2011 | |
|-------------------------------------|--|------|--------|--------|---------------------------------------|--------|-------------------|------------|------------|-------|
| | | Fall | Spring | Su | Fall | Spring | Su | Fall | Spring | Su |
| Train researchers, design protocols | | | | | | | | | a | |
| Phase I in Calculus I | | 1 | | 2 | | | Shadeo | d boxes a | are snap- | |
| Phase I in Calculus II | | | | 40m | | | shots in | 1 Phase | I and Pha | ase |
| Phase I in Engineering Physics I | | | X | - vile | Rucis | | II of cro | ss-section | onal studi | ies 🛛 |
| Analyze Fall '08 and/or Spr'09 data | | | | | C C C C C C C C C C C C C C C C C C C | 2 | in targe | eted cour | ses | |
| Phase I in Calculus III | | | | | | Mar | | | | |
| Phase I in Engineering Physics II | | | | | X | | 9/Dr | | | |
| Phase I in Differential Equations | | | | | | | I WE | San | | |
| Analyze Fall '09 and/or Spr'10 data | | | | | | | | ۹/ | | |
| Phase I in Linear Systems | | | | | la | | | | | |
| Phase II in Calculus I | | | | | NO MAR | - 0- | | | | |
| Phase II in Calculus II | | | | \sim | | Unan - | | | | |
| Phase II in Engineering Physics I | | | | | | | ann | | | |
| Phase II in Calculus III | | | | | | | a V ^{er} | PL | | |
| Phase II in Engineering Physics II | | | | | | | | Masa | Πn | |
| Phase II in Differential Equations | | | | | | | | | | |
| Phase II in Linear Systems | | | | | | | | | 1 | |
| Analyze Fall '10 and/or Spr'11 data | | | | | | | | | | |

The timeline is shown below. The arrows lines represent longitudinal studies in Phase I and Phase II.

Dissemination

The results will have interest from diverse audiences in science education, discipline-based educational research and problem solving research. Articles will be submitted to appropriate peer-reviewed journals. Throughout the project progress will be reported at conferences of NARST, AERA and discipline-based organizations focusing on educational issues, such as the Mathematical Association of America (MAA), Physics Education Research Conference (PERC) and American Society for Engineering Education (ASEE).

Project Evaluation

The Office of Educational Innovation and Evaluation, (OEIE) at KSU serves as the external project evaluator. OEIE has conducted numerous evaluations for state and national funded projects. Evaluators in OEIE have extensive expertise in program evaluation design, curriculum development, faculty training, instrument development and assessment of educational programs. Additional information is available at <u>www.k-state.edu/oeie/</u>. OEIE works with the project team to assess the achievement of project goals in a plan that aligns with the project implementation cycle.

The project evaluation determines the degree to which the project objectives are met using formative and summative evaluation strategies, including: 1) collecting data on program implementation, 2) assessing the viability of the research studies to be completed by the project, 3) assessing research reliability and replicability (how assessments developed in the research studies are used in the classroom) and 4) examining the project's contributions to problem solving and transfer of learning in STEM disciplines. Several overarching questions guide this effort.

- Are project activities being implemented as planned with results that lead to the accomplishment of project goals?
- In what specific ways are the project activities advancing toward the anticipated project goals? What strategies, people or specific activities account for this progress?
- Are the methodology and results of the research studies viable?
- Are the materials developed in this project replicable beyond the project?
- How has the project contributed to the theory of learning transfer and problem solving?

Formative evaluation will be utilized to provide regular feedback to project leadership regarding progress. The summative evaluation will assess overall project success. Findings will be used by the project team and funding agency personnel to determine the value as a pedagogical model for other efforts in STEM education. Project success is documented through:

- Examining the project documentation and research activities of the project and aligning them with the goals and objectives of the project.
- Validating the research data and the outcomes of the developed assessments.
- Examining potential for replication of the pedagogical and assessment strategies.
- Assessing the contributions of the project to the theory and methodology of STEM education.

This project evaluation: 1) utilizes multiple evaluation approaches; 2) draws on both qualitative and quantitative methodologies; 3) employs multiple evaluation research methods including questionnaires, interviews, classroom observations and examining documents from each of the three phases of the project; and 4) triangulates data for more robust findings.

Project team members work with the external evaluator to coordinate the overall project evaluation. Many of the components of this evaluation plan are embedded in the project implementation activities and project team members are involved in the data collection and analysis process. These data and their analysis are validated and compiled with those collected by the external evaluator to refine program activities, document program outcomes and provide information for NSF reports.

Project Personnel

<u>Dr. Dean Zollman (PI)</u>, Distinguished Professor of Physics, has over 30 years experience in physics education research and curriculum development. He has received international repute for his pioneering contributions in the field, particularly in the area of use of technology to help high school and college students learn complex physics concepts. More recently his research has focused on problem solving, conceptual learning and transfer in collaborative projects with the Co-PIs and other researchers including Dr. David H. Jonassen who is consultant (see below) on this project.

<u>Dr. Andrew G. Bennett</u> (Co-PI), Professor of Mathematics Education, has over 10 years experience on the use of technology in education. He is the founding director of the Center for Quantitative Education at Kansas State University and serves on the editorial board of the MAA Journal for Online Mathematics. The proposed research extends his prior work on data-mining techniques to measure conceptual understanding and transfer by using automated tools to provide real-time feedback on student learning.

<u>Dr. N. Sanjay Rebello</u> (Co-PI), Associate Professor of Physics, has over 10 years experience in physics education research, particularly in the area of transfer of learning. The proposed project extends work on two of Rebello's prior research efforts. The first, with Bennett as PI, investigated learning and transfer from mathematics to physics. The second project with David Jonassen at Univ. of Missouri focuses on case-reuse in problem solving in physics.

<u>Dr. Steven Warren</u> (Co-PI): Associate Professor of Electrical & Computer Engineering directs the Medical Component Design Laboratory. His educational research focuses on creation of technology that allows faculty to track student performance over time. He was worked with Dr. Bennett in implementing his online system in the Linear Systems course to track students from Mathematics to Engineering.

<u>Dr. David H. Jonassen</u> (Consultant), Distinguished Professor of Learning Technologies and Educational Psychology, University of Missouri, has over 30 years experience and international recognition in problem solving. He is author of several research articles and monographs on the subject. His theoretical perspectives have informed the project. He is currently collaborating with the PIs on a project investigating case reuse in problem solving. He will provide advice to the project staff on various aspects of research design.

In addition to the above personnel, the project will also hire three graduate students and a postdoctoral research associate. The graduate students and post-doc will work with the researchers on the project. Roles of each project personnel are described in the Budget Justification.

Results from Prior Relevant NSF-funded Research

DUE 0206923\$500,000June 01, 2002 – May 31, 2007Assessing Student Retention and Transfer in Mathematics, Physics and Engineering Courses

Activities: We created an online homework system to grade student work and provide substantial feedback in various mathematics courses. The system is NOT multiple-choice, but requires students to enter full solutions as numbers, functions and/or graphs. The system allows us to track student work for analysis and assessment of student learning. This system has now been extended to six classes (five in math and one in electrical engineering) and we have developed over 80 different assignments and have accumulated over 500,000 problems/responses from students and are accumulating more at over 100,000 problems/responses each semester. We have applied a variety of data-mining techniques (especially clustering algorithms and progressive linear models) to the data we have collected to analyze how students work in an online environment. We also carried out clinical interviews with students in math, physics and engineering course, to allow us to triangulate the findings from data-mining the results of the online system with evaluations of conceptual understanding from the interviews. In trigonometry we developed a model of conceptual understanding based loosely on the Van Hiele levels that rated students understanding on several levels (geometric, unit circle, functional). In differential equations we developed a model of understanding based on the APOS theory of Dubinsky. In physics courses we used contemporary models of transfer by Lobato and Bransford to assess the extent to which learners were able to transfer their knowledge from mathematics to algebra-based and calculus-based physics courses.

Findings: Combing data from the online system with conceptual learning as measured in clinical interviews and using clustering techniques (partitioning about medoids) we can identify three distinct groups of students. One group treats classes as a job and does exactly what they are assigned and nothing more. They do online assignments once and don't use the help system or go back and try again to improve their score. This group may or may not learn anything conceptually. They are doing what they are told and it is the teacher's job to tell them what to do to learn. That it is difficult to learn if you aren't trying to learn makes the teacher's job quite hard. A second group approaches learning the way we usually wish our students did. They try to understand the material, working problem sets a couple of times till they get it right, while making use of both online and offline feedback to improve their understanding. Not surprisingly, this group learns the most. A third group works harder than the other two groups, at least on the online materials. This group sees learning as a series of algorithms to be memorized. They do not believe they can understand the material since they don't have the necessary skills. But they can go over online problems over and over again until they have an algorithm for each type of problem memorized. However, their conceptual knowledge is the lowest of all groups. This is not surprising since they are not trying to understand conceptually; indeed they deny it is possible for them. Since these groups can be detected from their use of the online system, it is theoretically possible a system could identify how a student is trying to learn early in the semester (or perhaps recognize the student's type from a previous semester in an earlier course) and then adapt to the student to push them toward using more effective strategies. In particular, the last group might well learn more with less work if they could develop a sense they could actually understand the concepts, while the first group may need extra prodding to be sure they don't quit before they have learned. We pursue this research in Phase II of the project. Our transfer studies showed that students need contextual cues such as comparing similar abstract and contextual questions. While students could solve mathematics questions they were not able to set up the solutions to the physics or engineering question unless they were provided with cues to help them see how the math concepts applied in the situation. We pursue this research in Phase I of the project.

Capacity Building & Dissemination: The project produced two (2) M.S. theses in Mathematics, (1) one in Engineering as well a Ph.D. dissertation and two (2) M.S. theses in Physics. The project resulted in a book chapter, (Rebello, Cui, Bennett, Zollman, & Ozimek, 2007), four (4) peer-reviewed publications (Bennett, Lawrence, Neumann, Verbych, & Warren, 2007; Cui, Rebello, & Bennett, 2005, 2007; Ozimek, Engelhardt, & Rebello, 2004) and over 10 talks or posters at NARST, MAA, ASEE and PER conferences.