Understanding Student Pathways in Context-rich Problems

Pavlo D. Antonenko [a,*], John Jackman [b], Piyamart Kumsaikaew [b], Rahul R. Marathe [b], Dale S. Niederhauser [b], C. A. Ogilvie [b], and Sarah M. Ryan [b]

[a] *Oklahoma State University, Stillwater, OK 74078*
[b] *Iowa State University, Ames, IA 50011*

Abstract

In this paper we investigate the ways that students' problem-solving behaviors evolve when solving multi-faceted, context-rich problems within a structured, computer-based learning environment. During the semester, groups of two or three students worked on several problems that required drawing on more than one concept and, hence, could not be readily solved with simple "plug-and-chug" strategies. The problems were presented to students in a data-rich, online problem-solving environment that tracked which information items were selected by students as they attempted to solve the problem. The students also completed a variety of tasks, like entering an initial qualitative analysis into an online form. Students were not constrained to complete these tasks in any specific order. As they gained more experience in solving multi-faceted physics problems, student groups showed some progression towards expert-like behavior as they completed qualitative analysis earlier and were more selective in their perusal of informational resources. However, there was room for more improvement as approximately half of the groups still completed the qualitative analysis task towards the end of the problem-solving process rather than at the beginning of the task when it would have been most useful to their work.

Keywords: interactive learning environments, pedagogical issues, post-secondary education

1. Introduction

Progress in our technological society absolutely requires that young scientists and engineers have strong problem-solving skills that enable them to address new challenges that are often ill-defined and open-ended (King & Kitchener, 1994). Students, who are used to working on the well-structured, algorithmic problems typically presented in textbooks, struggle when confronted with the multiple challenges of more complex real world tasks. Typically they either approach the problem by searching for and using an algorithm that might work ("plug-and-chug"), freeze completely and immediately ask for direct help, or flounder along doing considerable busy-work with no real planning or direction.

* Corresponding author. Tel.: +1 405-744-8003; fax: +1 405-744-7758.
E-mail address: pasha.antonenko@okstate.edu (P. Antonenko).

We do not yet know which pedagogical methods might best help our students develop ill-structured problem-solving skills; however, insight can be obtained from research on differences between how experts and novices approach ill-structured tasks (Chi, Feltovich, & Glaser, 1981). Experts who successfully solve ill-structured problems tend to have strong, organized conceptual knowledge in the domain (Chi, Feltovich, & Glaser, 1981; Novak & Gowin, 1984), which allows them to begin the problem-solving process by qualitatively analyzing problems to quickly determine the main essence of the problem and avoid distraction from surface features and fine details that will not be needed until later in the solution (Reid, N. & Yang, M.-J., 2002; Schoenfeld, 1985). Experts also tend to have stronger, more generalized, metacognitive skills, which include monitoring the progress of their solution and reflecting on whether their chosen solution path is still potentially fruitful (Schoenfeld, 1985), as well as evaluation skills like understanding the importance of testing the solution against the assumptions during the solution process, and using extreme conditions to check the solution's validity. Strong problem-solvers also recognize the benefits of incorporating experiences gained from each problem into their knowledge-structure that can be useful to draw on when confronted with new ill-structured or multi-faceted problems (Bereiter & Scardamalia, 1993).

It seems likely that successful pedagogies for ill-structured problem-solving will draw from this expert/novice research to build on specific instructional methods that help students solve more well-structured problems (Gabel, 1993; Taconis & Hout-Wolters, 1999). A common practice in well-structured problem-solving instructional methods involves breaking the problem down into small steps, and explicitly teaching these steps to students. Such multistep problem-solving procedures have been developed in many domains such as, mathematics (Polya, 1957), chemistry (Bunce & Heikkinen, 1986), and biology (Hurst & Milkent, 1996). In physics, perhaps the first reported use in the literature was from Reif, Larkin, and Brackett (1976), where the explicitly taught steps were summarized as Description, Planning, Implementation, and Checking. This was extended by Halloun and Hestenes (1986), who showed that student solving performance improved with guided practice on these explicit problem-solving strategies.

This pedagogy can be taken a step further when a tangible space is provided for students to follow the explicit multistep procedure. For example Active Learning Problem Sheets (ALPS) devised by van Heuvelen (1991) contain separate, identified, sections where students must represent the problem graphically and develop a qualitative analysis before working on the mathematical representation. Also included are sections on evaluation of units and magnitude of answers. This approach has been transformed to a computer environment, the Hierarchical Analysis Tool (HAT), in which students are required to first choose the principles involved in the problem from a pull-down menu, then choose the associated concepts, and only then select the equations needed to solve the problem (Dufresne, Gerace, Hardiman, & Mestre, 1992; Leonard, Dufresne, & Mestre, 1996). This tool has been shown to help students both categorize problem types more effectively, and improve their problem-solving performance. A similar environment is provided by the Story Problem-Solving Environment (SPSE, Jonassen, 2004). With SPSE a story problem is presented to students who must then follow a series of tasks, ranging from identifying which scientific principles are involved, to qualitatively analyzing the problem, to building a quantitative representation of the problem.

In these examples students worked on well-structured problems in a constrained environment, and progressed through a series of pre-determined problem-solving steps. This research is extended in the present paper by observing how students approached moderately ill-structured problems in an online environment that did not constrain task sequence for solving the problem (Baker & O'Neil, 2002). Before describing our specific research questions, we review prior research on multi-faceted, context-rich problems as an intermediate challenge for students between well-structured and ill-structured problems. We also review prior work on tracking student pathways in unconstrained problem-solving environments.

1.1. Multi-faceted context-rich problems

Multi-faceted problems lie somewhere between well-structured textbook-type problems and large, ill-defined, open-ended real-world challenges with respect to the degree-of-difficulty that these types of problems pose for students. Multi-faceted problems require students to integrate *multiple* concepts in building a solution (Heller, Keith, & Anderson, 1992). Typically these problems are also context-rich, that is, they situate the student in a real-world challenge, for example: "You are a design engineer for a company that has been asked to build a ski ramp." However, the primary characteristic of multi-faceted problems is that they involve more than one concept, hence students cannot readily use a direct algorithmic (plug and chug) approach as they would in a traditional well-structured textbook exercise. The following is an example of a multi-faceted thermodynamic problem:

> *You are in charge of drinks at a picnic that will start at 3pm. You place ice inside a cooler at 6am, when the temperature outside is 10ºC. The day is forecast to warm up steadily to reach 30ºC by 3pm. Estimate how much ice you will need.*

Knowledge of at least two concepts is required to solve this problem: (1) heat transfer through a wall, and (2) the amount of heat required to melt ice. It is also moderately ill-structured, in that the problem statement does not specify the wall thickness of the cooler, or the material used. Students must recognize that they need this information for a final solution, and then look within the present resources to find that information. Although the problem is not mathematically complex, it does require that groups of students charged with solving the problem must discuss the nature of the problem, identify the main concepts that are involved, complete a qualitative analysis, locate or estimate the required information and, from there, develop their solution strategy.

The use of multi-faceted problems for instruction have been advocated by several groups across many disciplines for both K-12 and university use. Within physics this pedagogy has been developed by the physics education research groups at University of Minnesota (Heller, Keith, & Anderson, 1992) and Ohio State University (Van Heuvelen, 1991). Similar pedagogy has been used in chemistry (Reid & Yang, 2002), industrial engineering (Olaffson et al, 2003; Olaffson et al, 2004; Ryan et al, 2004; Ryan et al, 2007), and in several disciplines and at various grade levels by the Cognition and Technology Group at Vanderbilt (1992) and the IMMEX project at UCLA (Stevens, Ikeda, & Casillas, 1999; Stevens & Palacio-Cayetano, 2003; Stevens et al, 2004).

1.2. Tracking student pathways through a complex problem

The problem-solving environment we describe in this paper presents students with a general description of the task at hand, a menu of items that contain informational resources, and a list of task forms to complete as they make decisions about how to solve the problem. This environment is similar to the IMMEX online tool (Stevens, Ikeda, & Casillas, 1999) in that both information students need to solve the problem, and irrelevant information that is not useful are provided. Our problem-solving environment differs from the IMMEX tool in that we include a series of written tasks (qualitative analysis, verification and cross-checks) that the students complete as they solve the problem. The environment does not constrain students in the order in which they request information about the problem, or the tasks that they complete. Students are free to make decisions about how they approach the problem, with the assumption that if expert-like decisions produce student success, then these decisions may be "owned" by the students and be more likely to be used in future problem-solving contexts. The research advantage of the online tool is that we can track student pathways through these problems and establish the extent to which their problem-solving changes as a result of pedagogical interventions.

We build on work done by Stevens (2003) with IMMEX who showed that students start with a scattershot approach to requesting information in an unconstrained environment, but, with experience, they develop more expert-like strategies. Stevens and colleagues (1999, 2003, 2004) used a neural net to group solution strategies of high-school students solving chemistry and biology problems into characteristic approaches: (1) the Prolific strategy, whereby a student requests a broad range of both relevant and irrelevant information, (2) the Redundant strategy, in which a student requests information that s/he already has, e.g., for a diagnosis case, the student orders a test that provides information on an already eliminated diagnosis, (3) the Efficient strategy whereby a student tends to request pertinent information, and (4) the Limited strategy, in which a student takes a guess at the solution without having requested sufficient information. As students solved more problems, they tended to move away from the Prolific strategy, and toward the Efficient strategy. Similar improvements were noted by Chung and Baker (2002) as their students solved design tasks in an online environment.

We extend this work by examining when students report tasks they completed while solving the problem. Our specific research questions were; when do students complete their qualitative analysis of the problem: early in the solution when it may be most useful, or after they have settled on a solution process when it may be easier to complete the qualitative analysis task? We also sought to confirm the information-gathering result from Stevens and colleagues (1999, 2003, 2004) by examining which data resources students requested and when they were requested. Do the students follow a "prolific" strategy of collecting all available data early in the solution, or do they realize that for complex contextualized problems there is so much relevant and irrelevant data that this technique becomes less useful, and move to a strategy of determining what information is needed, and seeking only that information?

There are pros and cons to using online tracking of student pathways to explore how students solve problems. Individually observing and recording students in interviews provides much more information for each student group, but it is expensive and typically limited to monitoring only a few groups. It is also difficult to conduct sufficient interviews to observe the progress of students throughout a semester. Online tracking increases the size of the data sample while allowing data to be collected in context, that is in a normal class environment rather than in a lab setting. However, it also introduces complications. For instance, the time when students complete their description of a task via the web form can be well after when they actually did that work. We discuss this concern later in the paper. A potential confounding issue in the present study was that using the online environment and solving multi-faceted problems were both new to the student.

2. Data collection

2.1. Educational Context

The data presented in this study came from the Spring 2006 semester of a sophomore-level, calculus-based physics course at Iowa State University. Three hundred and fifty students took the course, which was taught by one of the authors of this paper (CO). Each week students in the course met for three lectures, one recitation, and one lab. The active-learning format of the lecture was approximately 10 minutes of mini-lecture about an idea, followed by a conceptual question (referred to as a concepTest (Mazur, 1997)) which the students answered via infrared clickers; first individually, then in a group discussion, and finally, recommitting to their solution as a group. The recitations used a mixture of Physics Tutorials (McDermott & Schaffer, 2002), and context-rich, multi-faceted problem solving activities (Heller, Keith, & Anderson, 1992) designed to increase ill-structured and multi-faceted problem-solving skills.

Each topic in the course followed approximately the same sequence: An introductory tutorial during recitation to address the main concepts, two to three lectures, a lab, and two problem sets. The first problem set was due early in the instructional sequence and contained mainly conceptual questions. The second problem set focused on standard end-of-chapter problems designed to reinforce and assess the basic procedural knowledge in the topic area.

Context-rich problems served as a capstone event for the topic area. Groups of two or three students (termed a “team” in this paper) worked on these problems during their recitation session where approximately 20 students meet with a teaching-assistant (TA). The TA’s role was to provide guided instruction on how to qualitatively analyze the problem (work from concepts and diagrams to design a solution). We taught the TA's how to use leading prompts in all their discussions with students, rather than simply giving students answers. At the start of the semester, this was a challenge for the TAs because they were inclined to provide more direct help to the students by suggesting an approach or to identifying the key constraint in the problem. We trained TAs to scaffold: to ask prompts (Xun & Land, 2004) that supported students in the early stages of the semester; such as: *(1) What information is missing? (2) How are … related to each* *other? (3) What do you think are the primary factors of this problem? (4) Why is it …? (5) Please explain.*

A weekly meeting, which included the instructor and the TAs, reinforced the TAs role as a guide rather than a direct information resource, but we did not assess the fidelity of the TA to the tutoring/scaffolding plan in the actual classroom.

Another key skill for students to develop was to monitor their solution as it progressed. Schoenfeld (1985) was one of the first to identify the difference between novices and experts in ongoing monitoring of their solution strategies. He analyzed many tape-recordings of students and faculty solving mathematics problems and found that experts periodically stopped to check if their strategy was making good progress, whether it was consistent with the original plan, or whether the algebra was getting too messy. Novices (and our students), on the other hand, plowed on regardless of how effectively the solution was progressing. During the semester whenever the lecturer solved a problem in class he modeled monitoring the progress of the solution. TAs were also encouraged to ask students to demonstrate how they were monitoring progress as they worked on the multi-faceted problems during recitations.

As the semester progressed, students worked on five context-rich problems; two on thermodynamics, one on waves, and two on magnetism and magnetic induction. The problem descriptions are given in Appendix A, the resources available to students for one problem are given in Appendix B, and more details on the problems can be provided upon request to the authors. Due to restrictions in computer class-room space approximately half of the recitation sections solved the problems in a pen-and-paper format, and half used the online Problem-solving Learning Portal (PSLP) environment described below (Olaffson et al, 2003; Olaffson et al, 2004; Ryan et al, 2004; Ryan et al, 2007). Tracking information from the PSLP allowed us to analyze how students approached the problems, including the order in which students gathered information, analyzed the problem, and identified the principles involved before submitting their solution.

Recitation sections met in a classroom that had one computer per team. The makeup of the teams was not actively managed by the TA; students self-selected onto teams, some teams stayed together during the semester, others reformed and students did not attend every recitation. The login page for PSLP required one student to start the problem, and others could then add their names. However, because teams did not always sign in their complete group, we treated the teams as anonymous and examined overall class behavior.

2.2. Problem-solving environment

The PSLP was developed by the authors to present ill-structured story problems in an on-line environment. The portal was designed as a flexible shell that could be populated with problem-scenarios from any content area. The initial screen presented the problem statement to the students (Figure 1). The customizable template for the PSLP included a menu bar across the top to provide access to the tasks students must complete as they solve the problem, and a menu bar on the left with lists of resources, tools, and advice information that provided guidance for solving the problem. In the present study students determined the sequence in which they filled in the tasks and accessed resources, though the order of the items in the task bar may have suggested a preferred order of completion for tasks to some students.

Insert Figure 1 about here

Resources were split into four categories: data, physical principles, diagrams, and advice. Each category contained some pieces of information that were relevant, and others that were irrelevant for solving the problem at hand. A list of resources available for our example problem is provided in Appendix B. Students were provided with a title for each resource that described the information which will be shown if the resource is accessed. Accessing each resource opened a new window — allowing participants to view several windows on their screen — but accessing resources also cost students "time" from their "time-remaining" account (top-left of screen). The problems were written in the second-person, i.e. "You are in charge of drinks at a picnic . . ." and were posed as a challenge to be met before meeting with another person in 90 "minutes" time. Accessing resources reduced this "time" account. Each piece of information typically cost between 5 and 10 "minutes." The "time economy" likely impacted students' decisions on which, and how many, resources students selected, but we have not yet quantified this impact.

Near the top of the screen was a task-bar where students selected a task and entered their work. These tasks included:

- Qualitative analysis: textual information written by students, in which they described qualitatively what physics processes take place in the problem.
- Relevant concepts: a set of check boxes where students selected concepts that directly applied to solving the problem.
- Ongoing monitoring: a text box where students described what checks they made during their solution.
- Solution: a set of radio buttons which typically included 15 different numerical values as possible answers to the problem.
- Problem review: a text box where students described what checks they have made after they obtained their solution.

Students could complete these task descriptions at any time in the problem and complete these tasks in any order. Resubmission of these tasks was allowed. There was also a Simulation: a Macromedia Flash simulation of the problem that was available to students only after they had submitted their solution. The simulation illustrated some quantitative aspect of the solution, e.g., the overall efficiency of the double engine used in Problem 2 (Appendix A). Students were warned that once the simulation was run they would not be able to change any of their answers.

3. Results

3.1. Resource Gathering

One essential aspect of successful problem solving is collecting and extracting relevant information from the resources at hand. In this section we discuss how students accessed information as they progressed through five physics problems from the beginning to the end of the semester. Table 1 presents basic information about the number of teams, total resources, and number of relevant resources for the five problems.

Insert Table 1 about here

Analysis of the system tracking data demonstrated that student teams tended to use only about 25% of the resources available to them across all 5 problems. Overall, the average fraction of resource pages accessed, while solving problems, decreased from problem 1 ($f_{resource} = 0.29±0.02$) to problem 5 ($f_{resource} = 0.22±0.02$). The average is taken across all teams and the error on the mean is reported. Furthermore, in problem 3, one team did not open any resources during their problem-solving process, and in problem 5 the number of such teams increased to seven. Teams that did not access any resources tended to submit incorrect solutions. These teams seem to reflect the “Limited” strategy class identified by Stevens and colleagues (2004), in which students made a guess at the solution without having requested sufficient information.

As the teams progressed through the semester, they displayed several distinct patterns of accessing information. For the first problem, many teams tended to open resource pages in the order that they were presented to them on the screen (i.e., top to bottom), viewing both relevant and irrelevant resources. Figure 2 shows a typical click-map for resource requests for problem 1. Each row corresponds to a team and the horizontal axis represents the series of page requests the team made to the server. If the page request was for a resource or the submission of the qualitative analysis task then a box is shown on the row. However, if the page request was a click on the PSLP task bar or submission of another task then no box is shown. Relevant and irrelevant resources accessed by the students are coded by different shadings. Dark boxes correspond to requests for relevant resources while light boxes are requests for irrelevant resources. The circles show the “clustered” pattern of accessing resources. The submission of the qualitative analysis is shown as a cross-hatched box.

Insert Figure 2 about here

A “cluster” of requests is defined as an uninterrupted sequence of 3 or more resource requests. Clusters of requests indicated that teams were not interrupting the resource gathering process to work on the task pages. This pattern changed, however, as the semester progressed. The percentage of teams who exhibited a “clustered” pattern of accessing resources (Figure 1) was (39±7)% in problem 1. This significantly decreased in problem 2, (24±7)% of teams, and disappeared almost completely in problem 3, (5±5)% of teams, problem 4, (3±3)% of teams, and problem 5, (3±3)% of teams. The quoted errors are the errors on the mean for a binomial distribution, i.e. a team either clustered or did not. This result confirms what Stevens et al.[Error! Bookmark not defined.] found with students working in the IMMEX environment: that they moved from "prolific" gatherers of many resources in a sequence, to a behavior that intersperses resource gathering with other tasks.

A positive correlation was found between whether a team accessed resources as clusters and f_{resource} for a team. For problem 1 this correlation was very strong: r = 0.552 and p = 0.01. Thus, the likelihood that students would view resources in clusters increased with the amount of resources that were opened by the students.

The fraction of relevant resources that were accessed helps to differentiate the behavior of teams. A negative correlation was found between f_{relevant} and f_{resource}. For problem 1 this correlation was r = -0.406 with p = 0.01, i.e., more expert-like teams who accessed a larger fraction of the relevant resources, accessed a smaller fraction of the total resources.

A key question is whether more teams demonstrated this behavior as the semester progressed. Figure 3 demonstrates that the average fraction of relevant resources opened increased from $\bar{f}_{relevant}$ = 0.78 (problem 1) to 0.85 (problem 3), although the error on these means indicates that this difference was not significant.

Insert Figure 3 about here

Another pattern of accessing information resources can be inferred from the type of information that was viewed. Most of the resources available to students in the PSLP were presented in two categories: a) data, and b) principles. While the data resources comprised the bulk of information accessed by the teams across all five problems, the fraction of physics principles resources increased significantly in problems 3, 4, and 5 *(Figure 4).* This can be demonstrated by calculating the average $f_{\text{principles}}$ for the first two problems compared to the last three: $f_{\text{principles 1-2}} = 0.11\pm0.01$ and $f_{\text{principles 3-5}} = 0.25\pm0.03$. The data indicate that students access more information on physical laws and principles for the later problems.

Insert Figure 4 about here

Taken together, these results indicate that as students gained more experience in solving multi-faceted physics problems, requests for information were less likely to come in uninterrupted clusters, and students tended to access more information on physical laws and principles. There was, however, no significant change in the fraction of relevant resources that the students accessed.

3.2. Completion of Tasks

PSLP tracking data showed that as students were solving the problem, they tended to complete the tasks in the order that was presented to them via the task bar (shown in Figure 1). Table 2 indicates that the order of mean completion times was the same for all five problems. The table shows the average time and the error on this mean for completing the tasks, with time=0 corresponding to the beginning of each team's problem session.

Insert Table 2 about here

As noted in an earlier section, we recorded the time that the teams entered their analyses via web forms, which occurred after teams discussed the task. From the closeness of the times for ongoing monitoring and solution, it seems that students were describing what they did for ongoing monitoring well after they may have done this task. In contrast, the submission times for the qualitative analysis and relevant concepts were separated from the solution time by 10 to 15 minutes, indicating that students had still not finished working on the problem when they entered their description of these tasks.

It is notable that the average completion time for the qualitative analysis task decreased from 41 minutes in problem 1, to 29 minutes in problem 5. This persisted even when normalizing for the time each group submitted their problem solution: $(t_{QualAnal}/t_{solution}) = 0.78$ for problem 1 and $(t_{QualAnal}/t_{solution}) = 0.61$ for problem 5. Thus, the qualitative analysis was completed 20% earlier in problem 5 than in problem 1.

Experts tend to conduct an early qualitative analysis of the problem and use this to determine which resources (data, principles) are needed to solve the problem. A more novice-like behavior is to first collect many of the resources (both relevant and irrelevant), work on the problem, and after the problem is largely solved, formalize their thinking on the qualitative nature of what the problem was about. The idea that novices would complete a qualitative analysis as a summary task was suggested to the authors by VanLehn (2005) due to the likelihood that there is reduced cognitive load on novices to perform a qualitative analysis after they have spent significant amounts of time working on the problem. Savelsbergh and colleagues (2002) used this idea in a pedagogical approach where students re-represent the problem as a schematic sketch after the problem has been solved instead of before.

To explore this further we examined the relative time between when students completed the qualitative analysis section and when they requested resources. We computed the time when each team had reached 80% of their total resource requests and compared that with the time they completed the qualitative analysis. Both times were normalized for each team using the total problem solving time. Figure 5 presents a scatterplot for problem 1 of normalized time viewing 80% of resources versus the normalized time submitting qualitative analysis. Each point corresponds to a single team.

Insert Figure 5 about here

In the top left region of this scatter-plot we find teams that completed their qualitative analysis before requesting 80% of their resources. This would be considered more expert-like behavior of using a qualitative analysis to inform which resources to gather. The bottom-right of this scatter-plot comprises teams that submitted their qualitative analysis after gathering 80% of their resources, and in some cases, after submitting their solution (normalized times > 1). The lower-right group either found it cognitively easier to do their qualitative analysis after they had completed a large amount of work, or they did this task earlier but completed the qualitative analysis task portion of the assignment just before entering their solution.

Clearly there are two classes of behavior separated by the diagonal line, with the more expert-like teams in the top, left section. A key question is whether student teams changed their behavior as the semester progressed. We calculated the percentage of teams who fell into this top, left section (expert-like) for each of the 5 problems, i.e., teams that completed qualitative analysis before they viewed 80% of the information resources. This fraction changed from 26% of the teams in problem 1 to above (or near) 50% of the teams for subsequent problems. The error on the percentage of teams is the binomial error on the mean, i.e. a team either shows expert-like or novice-like behavior. Following the initial shift between problems 1 and 2, there does not seem to be a consistent trend for later problems. Performance of groups who entered a correct answer is also shown in this table: this fraction did not significantly differ between the two types of teams. We also found that teams that submitted their qualitative analysis earlier tended to have a higher value for f_{relevant} (r = -0.389, p = 0.01), indicating that they were more effective in choosing relevant resources—also the type of behavior one would expect from experts.

Insert Table 3 about here

A further question addresses whether teams accessed the resources that described physics principles before they accessed the data resources and before they submitted their qualitative analysis. Table 4 shows that, for most problems, principles were requested after the data resources (the exception was problem 4). Both times were typically earlier or comparable to when the groups submitted their qualitative analysis. Note that not all groups requested principles resources (Figure 4).

Insert Table 4 about here

The comparison of times for requesting physics principles versus the mean time for requesting data resources can also be examined by plotting each group’s mean time. The scatter plot for Problem 1 can be seen in Figure 6. There is a correlation between whether a team requested information early, and whether the team requested both types of information (data and principles) early. This correlation was observed for the other problems as well. Further, in many cases principles were requested after data resources (teams in above the diagonal of this scatter plot). One possible hypothesis for these late-time principles requests is that the group may be stuck or unsure about an aspect of the problem and request some conceptual information. This conclusion, however, is beyond the scope of the present study and requires verification through additional research.

Insert Figure 6 about here

We also examined the relationship between when teams submitted their qualitative analysis and when they requested physics principles (see Figure 7 for scatterplot of Problem 1). There was a weak correlation between the two times with some groups requesting information on the principles after they submitted their qualitative analysis (teams to the right of the diagonal line). This trend continued in Problem 5 (see Figure 8) where a proportionally larger number of teams also requested principles after their qualitative analysis. One hypothesis is that these groups struggled with a specific aspect of the problem that did not make sense to them and returned to the principles resources to seek clues to rectify their confusion.

Insert Figure 7 about here

Insert Figure 8 about here

4. Summary

In this paper we described a problem-solving environment for multi-faceted problems. Our PSLP extends previous tools by including both a large collection of relevant and irrelevant resources available to students, as well as providing web-based forms for students to describe the tasks they are completing as they solve the problem. Students can complete tasks or select resources in any order and hence are free to make decisions about how they approach a problem. The key goal of this paper was to establish the extent to which students moved from novice to expert-like behavior as they gained more experience in solving moderately ill-structured problems within this environment.

The problem-solving pedagogy used in this paper was introduced by Heller and colleagues (1992) where students worked on context-rich, multi-faceted problems with guided instruction from TAs. Groups of two or three students solved problems that involved more than one concept and could be more readily solved when students utilized more expert-like strategies of qualitative analysis and planning. These strategies were explicitly taught by the TAs, as were ongoing monitoring and reviewing strategies.

As students gained more experience in solving multi-faceted physics problems, their requests for information were less likely to come in uninterrupted clusters, and the data indicate that students access more information on physical laws and principles for later problems. There was however no significant change in the fraction of relevant resources that the students accessed. Student groups also complete their qualitative analysis of the problem 20% earlier in the last problem of the semester when compared to the first problem, though the task was still successfully completed by many groups after they had accessed most of the resources. The fraction of groups who completed the qualitative analysis task towards the end of the problem decreased from 75% for the first problem to close to 50% for the rest of the problems. This finding warrants further study since the fraction of groups who arrived at a correct answer did not significantly differ based on the expert-like characteristic of early completion of the qualitative analysis task. We also note that completion of the qualitative analysis task (as well as the ongoing monitoring) was assessed through submitting a description in a text web-form. Hence the task submission occurred after students had performed the task while solving the problem.

Addressing our main research goal, these observations indicate some shift towards more expert-like behavior in that, for problems completed later in the semester, students tended to perform qualitative analyses of problems earlier and tended not to gather information in uninterrupted, indiscriminate sequences. This finding can be used by the physics education research community as evidence for the impact of having students practice solving complex problems under TA guidance. However much remains to be examined: videos of student groups may provide additional insights into students' problem-solving behavior, we need to assess the impact of familiarity with the environment, and examine more closely the role and fidelity of the TA.

Pedagogically there is also room for improvement: approximately half of the groups still completed the qualitative analysis task after they examined many resources. The easiest strategy to implement may be to have TAs encourage student groups to complete their qualitative analysis earlier. However, TAs typically have responsibilities for many groups during each session, and may not be able to provide groups with timely advice. We are currently examining ways to automatically analyze the behavior of each student group in real-time and have the PSLP provide hints and assistance to students (Ryan et al, 2007). For example, if a group appears to be indiscriminately opening all data resources, the PSLP server would send a pop-up window suggesting that they perform a qualitative analysis of the problem. A further option would be to provide feedback on the substance of the typed qualitative analysis with automatic text processing. Rose and colleagues (2006) have used text-classification software that, when trained on a large set of prior student answers, can be used to give feedback in real-time to students when they enter their qualitative analysis. The online problem-solving environment PSLP has great potential for providing this feedback to students as they develop their problem-solving skills. PSLP is also designed to be used in any discipline: the types of tasks and resources can be reconfigured for use in other subjects. Faculty interested in using the tool should contact the authors.

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Appendices

Appendix A: Problem Descriptions

1. "How much ice will you need?" You are in charge of keeping the drinks cold for a picnic. You have a styrofoam box that is filled with cola, water and you plan to put some 0° ice in it. Your task is to buy enough ice to put in the box at 6am so that the temperature stays at 0°C until the picnic starts at 4pm. You don't want to buy too much ice because that means that you'll have less money to spend on food and other picnic items.
   How much ice will you need? You have 90 "minutes" to calculate the amount of ice, before your cousin picks you up to drive to buy the ice. Getting information from the resources (on left-hand panel) may cost you some 'time'. The resources will only cost you " time" when you first access them and the cost will be always indicated. Your score will depend partially on how much 'time' you have left in your account.

2. "Optimal Operating Conditions" You are an engineer designing a nuclear power plant. The core of the reactor is designed to operate at a temperature of T_H and the cooling water is at a temperature of T_C. Your group has found that you may be able to reduce the cost of the plant considerably by using smaller engines to convert the heat from the reactor into work in the form of electrical energy. The design concept you have developed is to use a tank of liquid lithium as heat buffer to be held at temperature T between T_H and T_C and then use one generator to operate between the core and the lithium tank and another to operate between the tank and cooling water.
   In 90 mins you are to present your idea to the engineering committee which is to decide whether a full scale engineering study of this design is to be undertaken. You need to develop the case for this design, including what temperature T for the lithium tank produces the greatest efficiency and how does this efficiency compare to the standard design.

3. "Making a perfect fifth" Your friend, an artist, has been thinking about an interesting way to display a new wind sculpture she has just created. In order to create an aural as well as visual effect, she would like to use the wires to hang the sculpture as sort of a string instrument. Her basic design involves vertically hanging two pieces of wire from two eye-hooks on the ceiling, then hanging the heavy sculpture from a horizontal bar from some point along the bar. The distance between two eye-hooks on the ceiling is the same as the total length of the horizontal bar.
   The aural effect that she would like to achieve is that when the wind blows across two vertical strings, they play a perfect fifth, i.e. the ratio of the frequencies of the two sounds is 3:2.
   Your friend tells you that she has been successful in hanging the sculpture but not in choosing the point along the bar to hang the sculpture giving the desired sound. Desperate for success, she knows you are taking physics and asks you for help.

In 90 minutes you are due to meet her at the local coffee shop. What is your advice concerning the design of the sculpture. What notes will the two strings play with your design?

4. “Designing a blood-flow meter” You have a summer internship at a company that makes medical instruments. During medical surgeries, there is a need to measure the amount of blood flow through arteries that have been exposed by the surgery, but otherwise have not been cut. That is, blood is still flowing through these arteries.
   You know from your studies of biochemistry that blood contains a reasonable amount of both positive and negative ions. If you place a small magnetic field across the artery, then these moving ions would experience a magnetic force. Your company also manufactures a range of devices that can measure the electrostatic potential between two points.
   In 90 minutes you are due to meet with your boss. You need to sketch out a device that could provide the blood flow based on the measurement of the electrostatic potential across two points on the artery. Based on the model you develop, what electrostatic potential would you expect to observe? For the device to be practicable it needs to respond relatively quickly, so you should also estimate the order of magnitude of time it takes for the electrostatic potential to develop across two points on the artery.

5. “How will the utility company detect the theft” You are helping out during the summer at a relative's farm. In one corner of the farm are some high-tension power lines. Having aced Phys 222, you know that each power line will be surrounded by a magnetic field that changes with time. You wonder whether you could use this to induce an emf in a coil, and use the induced emf to drive some of the farm equipment. To test this idea you construct multiple loops of wire and connect it to an AC voltmeter.
   In 90 minutes you are due to show your relative your loop, your measurements and an explanation of how this works. What induced emf will you measure? Your relative will also want to know whether this is really power for free, or how could the utility company detect the theft of this power.
   Note: neither the Physics Dept at ISU, nor your instructor endorses this method of obtaining power.

Appendix B: List of resources available to students for Problem 1

Data

a) dimensions of box (10 min)
b) insulating properties of Styrofoam (10 min)
c) amount of drinks, water (5 min)
d) heat capacity of water, ice (5 min)
e) latent heat of fusion of water (5 min)
f) words describing temperature forecast for the day (10 min)

Physical Principles and Equations

a) temperature increase and specific heat capacity (5 min)
b) latent heat of fusion (5 min)
c) equation of state of materials (5 min)
d) zeroth law of thermodynamics (5 min)
e) first law of thermodynamics (5 min)
f) 2nd law of thermodynamics (5 min)
g) Heat conduction (5 min)
h) Heat convection (5 min)
i) Heat radiation (5 min)

Diagrams

a) sketch of box, including dimensions (10 min)
b) graph of temperature forecast for the day (10 min)

Ask the experts for advice

a) How to plan a good picnic (10 min)
b) How to solve a complex physics problem (10 min)
c) How to setup a thermodynamic problem (10 min)

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