AC 2008-184: FACILITATING PROBLEM-SOLVING TRANSFER IN PHYSICS

David Jonassen, University of Missouri

Dr. David Jonassen is Distinguished Professor of Education at the University of Missouri where he teaches in the areas of Learning Technologies and Educational Psychology. Since earning his doctorate in educational media and experimental educational psychology from Temple University, Dr. Jonassen has taught at the Pennsylvania State University, University of Colorado, the University of Twente in the Netherlands, the University of North Carolina at Greensboro, and Syracuse University. He has published 30 books and numerous articles, papers, and reports on text design, task analysis, instructional design, computer-based learning, hypermedia, constructivist learning, cognitive tools, and problem solving. His current research focuses on the cognitive processes engaged by problem solving and models and methods for supporting those processes during learning.

Young Hoan Cho, University of Missouri

Carlos Wexler, University of Missouri

Facilitating Problem-Solving Transfer in Physics

Problem: Learning to Solve Problems

The most common method for teaching physics classes in universities is the worked example of how to solve textbook story problems. Story problems consist of numerical values describing entities embedded in a thinly described context. In a worked example, the professor models the process for solving problems. A substantial corpus of research has shown that worked examples of problem solutions that precede student practice facilitates learning to solve problems by reducing the cognitive load and helping learners to construct problem-solving schemas [1,2].

Worked examples, like most approaches to problem-solving instruction, assume that the learners induce or construct a schema for particular kinds of problems following demonstrations of the process. However, in the worked example teaching process, students learn to translate relationships about unknowns in the problem statement into equations (direct translation strategy), solve the equations to find the value of the unknowns, and check the values found to see if they satisfy to original problem [3]. So the schemas that students construct are process schemas that are bereft of conceptual understanding. Process schemas are procedures to be memorized, practiced, and habituated and that emphasize answer getting, not meaning making [4]. When problem solvers attempt to directly translate the key propositions in the problem statement into a set of computations, they more frequently commit errors, because problem solving requires the capacity to recognize the deep structure of the problem [5].

If we assume that the implicit goal of all problem-solving instruction is the transfer of problem solving skills to new, contextually divergent problems, then how do we help undergraduates better understand the deep structure of problems? In order to transfer problem solving, learners access their schema for a particular kind of problem and analogically map it onto the target problem. If they generalize the correct problem schema to the target problem, then the solution process is a matter of applying the solution portion of the problem schema to the new problem. However, schema transfer faces three difficulties: over-reliance on quantitative problem representations and under-reliance on qualitative representations, mapping the incorrect problem schema to the target problem, and the over-reliance on single analogues.

In addition to quantitative problem representations, students need to construct qualitative (semantic) representations of problems. The "ability to construct and coordinate qualitative and quantitative problem representations is a precondition for successful and efficient problem solving in physics" [6]. Qualitative and quantitative representations are complementary. When solving physics problems, for example, qualitative problem representations are necessary prerequisites to learning quantitative representations [7]. When students try to understand a problem in only one way, especially when that way conveys no conceptual information about the problem, students do not understand the underlying systems they are working in. So, it is necessary to support conceptual understanding in students before solving problems by helping them to construct a qualitative representation of the problem as well as a quantitative one.

A second difficulty in generalizing schemas during transfer is the tendency of student to generalize problem solutions based on surface level similarities among problems [8, 9, 10, 11]. When humans are reminded of similar events by accessing them from long-term memory, that access is based more on surface commonalities than deeper level, structural commonalities[12]. Ross [13] found that superficial similarity influences retrieval of examples in statistics problems. People fail to recall relevant examples, especially when the two case differ in surface features, because people focus on surface features [14, 15].

A third impediment to schema generalization is the overuse of single analogues during instruction. Even though Sweller recommended multiple worked examples, the most common form of problem-solving instruction is the demonstration of a single problem followed by a practice problem. Traditional approaches to problem-solving instruction assume that people can abstract portable schemas from single examples and apply them to transfer problems. Loewenstein, Thompson, and Gentner [16] showed minimal transfer from a single example. Unfortunately, transfer from a single problem is insufficient for schema induction. However, over two decades of research has confirmed an advantage for comparing two cases over studying examples separately, a process known as analogical encoding.

Analogical Encoding

Analogical encoding is the process of mapping structural properties between multiple analogues. Rather than attempting to induce and transfer a schema based on a single example, Gentner and her colleagues have shown that comprehension, schema inducement, and long term transfer across contexts can be greatly facilitated by analogical encoding, comparison of two analogues for structural alignment [16, 17, 18, 19]. When learners directly compare two examples, they can identify structural similarities. If presented with just one example, students are far more likely to recall problems that have similar surface features. Analogical encoding fosters learning because analogies promote attention to commonalities, including common principles and schemas [20]. During analogical encoding, students must compare analogous problems for their structural alignment. Problems are structurally aligned when the relationships (arguments) among problem elements match [18]. Despite the consistent results from analogical encoding research, there remain unresolved implementation issues. The first unresolved issue in analogical encoding is how generalizable it is. The vast majority of analogical encoding research has required learners to map relatively simple, context-independent problems (e.g., Duncker's X-ray problem) to test their understanding of single structural relationships [21]. Some analogical encoding research has focused on real-world negotiation problems [16, 19, 22], however those problems focused on only one or two structural comparisons among analogues. Although analogical encoding has been consistently shown to facilitate schema induction and transfer in simpler, domain-neutral problems, analogical encoding has not been tested with more complex STEM problems that have multiple structural relationships in the problem. Therefore, our research proposes to examine the efficacy of analogical encoding with more complex, context-dependent problems in physics.

The second unresolved issue in analogical encoding is how to elicit depth in the comparison process. Because learners typically compare problems based on surface level characteristics, learners do not tend to structurally align problems [16]. However, Spencer and Weisberg [23] showed that presentation of multiple source analogs is not sufficient to ensure transfer across contexts. Merely reading or receiving multiple cases is not enough to produce comparison effects [16]. So, a" fruitful avenue of research may involve searching for ways of helping learners to focus on relevant features of training examples in a variety of domains and to learn to reliably identify these features in transfer problems" [17]. A limited body of research has examined methods for facilitating analogical encoding. In order to support that comparison process, different studies examined the physical juxtaposition of cases [24], using software [25], similarity ratings [26,] directed questions [17], describe commonalities [20], joint interpretation and alignment [27], and completing a diagram [22].

Again, with complex problems, we are not certain how effective these methods would be. Structural alignment with more complex problems requires more systematic approach to analysis because of the complexity of the problems. Therefore, we are examining how to support analogical encoding by asking students questions that require them to structurally compare problem pairs.

Questions

Questioning is one of the most fundamental cognitive components that guide human reasoning [28]. The threads of coherent reasoning are built around questions that humans ask and the answers they receive. Answering deep-reasoning questions articulates causal chains; goals, plans, and actions; and logical justification [28]. The question-answer rhetorical structure is the most common dialogue pattern in naturalistic conversation [29]. Question-driven explanatory reasoning predicts that learning improves to the extent that learners generate and answer questions requiring explanatory reasoning [29]. Questioning is grounded in discourse theories of informal reasoning, and it is an essential process involved in problem solving, especially design problems 30. Questions arise in reciprocal relationship to decisions that must be made while solving problems.

Our research proposes supporting analogical encoding through questioning provided by a point-and-query system for selecting questions relevant to problem pairs. Catrambone and Holyoak [17] provided schema oriented questions to help learners focus on problem-relevant aspects of the story. They found that presentation of extensive comparison questions along with three analogs sufficient to enable transfer to superficially dissimilar target in the absence of hints. Our research questions include:

- Will analogical encoding improve problem-solving transfer in a physics course?
- Will analogical encoding conceptual understanding of physics problems?
- Will questions effectively enhance analogical encoding processes in a physics course?

Methods

Participants

The participants in this study were enrolled in Phys 1210 (College Physics I), a 4 credit-hour, algebra-based physics at a Midwestern (U.S.) university. A total of 207 students (108 male, 99 female) began the course. Only 177 completed the course. This level of attrition is common for this type of course. The participants included sophomore, junior, and senior Pre-med, pre-vet, and many other non-science majors (age, class, and major data were not available). Like most introductory physics courses, Phys 1210 covers kinematics, dynamics, fluids, oscillatory motion, waves and thermodynamics. Data were collected throughout the spring, 2007 semester.

Instruments

Assessment instruments included standard examinations for the course that included both quantitative problems and conceptual questions. Embedded within these examinations were calculation questions (see example in Figure 1) and conceptual questions requiring comprehension of the relationships among problem elements but no calculations (see example in Figure 2). These exams were time-restricted and completed during normal classroom periods during the semester. Student exam scores were calculated by adding the point values achieved by the students on all of the calculation questions plus the conceptual questions that were related to the treatment. Examinations were graded by teaching assistants using standard answer rubrics. For example, on the first exam in the course, student scores on problem 1 and questions 1, 2, and 5 were summed to provide the dependent variable for the first unit (dynamics). The same kind of assessment was conducted for each of the other four units, work and energy, linear momentum and collisions, fluids (only sections related to the continuity equation and Bernoulli's theorem), and thermodynamics.

Part I **[10 points**, a similar question was posed in your last pre-lab]: Consider a calorimeter (an insulated device so that heat does not flow in or out). We place 2 kg of liquid nitrogen on it (latent heat of vaporization Q_v =199 J/g at T_v = 77.2 K). You then place a piece of metal of mass m = 0.23 kg originally at room temperature (T_r = 25 °C) in the liquid nitrogen. You then measure that 0.13 kg of the nitrogen evaporates when equilibrium is reached. Calculate the specific heat of the unknown metal (express your answer in J/kg °C).

Figure 1. Sample calculation question embedded in examination.

Which one of the following factors is directly responsible for the pressure exerted by a confined gas? (**choose one**)

1. the atomic mass of the gas
2. the density of the sample of molecules
3. the temperature of the sample of molecules
4. the collision of gas molecules with the sides of the containing vessel
5. the average translational kinetic energy of the molecules

Figure 2. Sample conceptual question embedded in examination.

Additionally, students completed pretest and posttest administrations of the Force Concept Inventory [31]. The Force Concept Inventory (FCI) is a multiple-choice test designed to assess student understanding of basic concepts in Newtonian physics. The primary purpose of the FCI is to evaluate the effectiveness of instruction.

Materials

All instructional materials were presented to students on the course website, developed in WebCT, which was used to deliver all materials and assignments in the course except for the examinations. During five units covered throughout the course, including Dynamics (Newton's laws and applications), Work and energy, Linear momentum and collisions, Fluids (only sections related to the continuity equation and Bernoulli's theorem), and Thermodynamics (only sections related to thermal cycles and the 2^{nd} law of thermodynamics), students were assigned to complete a "Conceptual Test." In each conceptual test, a pair of problems taken from a textbook not used by the students in this class was presented (see Figure 3 for problem pair presented during the study of linear momentum and collisions). Following the presentation of each problem pair, several questions (Range = 7-17) were presented requiring students to compare the each problem in the pair for structural alignment (see Figure 4 for sample questions related to linear momentum and collisions). These questions asked students to compare problem pairs on conceptual attributes of each problem. Because each question was asked about each of the problems in the pair, they required students to compare the problems related to the relationships examined by the question. That is, each pair of questions required students to analogically compare a pair of problems. No feedback was provided to the students about the correctness of their answers. Students' responses to each question were automatically collected and summarized for each student by WebCT and made available for analysis.

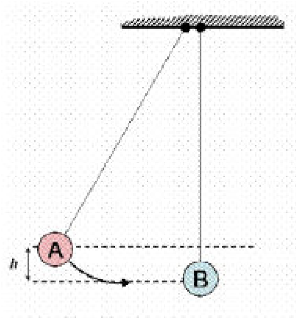
Procedure

Consent to participate in the study was collected through a link on the course website. After reading about the requirements of the study, all students agreed to participate.

Data were collected during the completion of five units in the course, including Dynamics (week 4), Work and energy (week 6), Linear momentum (week 7), Fluids (week 12), and Thermodynamics (weeks 14-15). These units were selected to represent a broad variety of physics concepts normally taught in an introductory course. Each unit was studied by the students for one to two week periods prior to moving on to the next unit. In addition to the Conceptual Tests described before, students attended lectures, read textbook assignments, and met with teaching assistants during recitation sections. A limitation of this study is that we were unable substantially alter the pedagogy of the course because of students expectations about methods and workload. Classroom expectation pose a serious limitation to all in situ classroom research.

PROBLEM 1

Two pendulum bobs (see figure) are made of soft clay so that they stick together after impact. The mass of bob A is half of that of bob B. Bobs A and B are initially at rest, with bob A starting at a height *h* relative to bob B. What is the merged blob (A+B) speed immediately after the collision?



PROBLEM 2

A 10-g bullet traveling at a speed v_0 = 76 m/s is fired towards a 1-kg block of wood supported by an ideal wire. The bullet penetrates the block of wood where it gets embedded. What is the speed of the bullet + block system immediately after the collision?

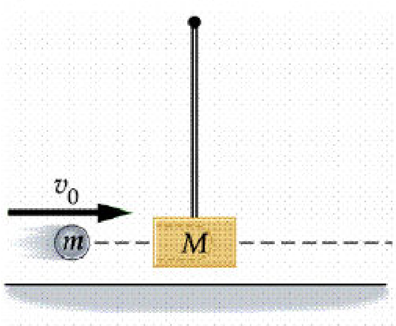


Figure 3. Problem comparison for linear momentum and collisions unit.

The Force Concept Inventory was completed by students during the first week of the class and again during the tenth week of class. Material covered subsequent to the tenth week were not addressed by the FCI.

Results

Student scores on the Conceptual Tests were generated by WebCT and are presented in Table 1. On average, students score 71% on the Conceptual Test assignment, with a range of 60% to 83%. This variability is common in introductory physics courses, owing to the differential complexity of the material being learned in the course and the myriad individual differences that mediate that learning. However, in this study, students scored lowest on the work-energy assignments, even though work-energy concepts are seldom regarded as the most difficult.

Q1-3. In PROBLEM 1, before the collision happens, as bob A is dropping towards bob B, which of the following physical quantities change? (Select all that apply). a.) Gravitational Potential Energy b.) Kinetic Energy c.) Mechanical Energy d.) Linear momentum e.) None of the above ANSWER: a, b, d	Q2-3. In PROBLEM 2, immediately after the collision the bullet + block start to raise. Which of the following physical quantities change during this process? (Select all that apply). a.) Gravitational Potential Energy b.) Kinetic Energy c.) Mechanical Energy d.) Linear momentum e.) None of the above ANSWER: a, b, d
Q1-4. In PROBLEM 1, after the collision happens and the bobs move together, which of the following physical quantities change? (Select all that apply). a.) Gravitational Potential Energy b.) Kinetic Energy c.) Mechanical Energy d.) Linear momentum e.) None of the above ANSWER: a, b, d	Q2-4. In PROBLEM 2, you are now asked to determine the height attained by the bullet + block system after the collision. What physical principles would you use to solve this (assuming that you already solved the original problem stated above) (Select all that apply) a.) Newton's Second Law of Motion b.) Torque and angular velocity c.) Kinematics of 2D motion d.) Conservation of Mechanical Energy e.) Conservation of Linear Momentum f.) Other ANSWER: d

Figure 4. Question prompts for structurally comparing linear momentum and collisions problems.

Individual students scores for each of the Conceptual Tests were regressed onto the examination scores (see Table 2). For every assignment, the students' scores on the Conceptual Tests significantly predicted performance on the examination questions. The student scores on the treatment activity accounted for a range of 4.8% to 19.2% of the variance in student performance on the examination questions related to the treatment.

Treatment	Total	Mean	StdDev
1	17	12.88	2.78
2	10	8.27	1.87
3	14	9.21	2.41
4	11	6.57	1.97
5	18	13.71	3.83

Table 1. Descriptive statistics on treatments (Conceptual Tests).

In order to assess the effects of the analogical encoding activity on problem solving vs. conceptual understanding, we split out the results on the two kinds of questions for practice assignments 1, 3, and 5 (see Figure 3). In all three exams assessing understanding of all five units, performance on the analogical encoding practice significantly predicted problem-solving performance, accounting for approximately 10% of the variance for each problem. However, in only two of the three exams did the analogical encoding practice significantly predict performance on the conceptual questions, and those were barely significant at the .05 level, accounting for only one or two percent of the variance.

Model	SumSquares	df	MeanSq	*F*	Sig	R^2
Exam 1 Regression	1589.47	1	1589.47	26.64	.000	.115
Exam 1 Residual	12231.74	205	59.67			
Exam 2 Regression	139.97	1	139.97	9.60	.002	.048
Exam 2 Residual	2798.41	192	14.57			
Exam 3 Regression	1249.99	1	1249.99	15.04	.000	.075
Exam 3 Residual	15372.71	185	83.09			
Exam 4 Regression	1610.76	1	1610.76	41.59	.000	.192
Exam 4 Residual	6777.45	175	38.72			
Exam 5 Regression	615.15	1	615.15	21.58	.000	.109
Exam 5 Residual	5017.10	176	28.51			

Table 2. Regression analyses of assignments scores onto examination scores.

Only 153 students completed both administrations of the Force Concept Inventory. Because the test was administered during recitation sections, which were not required, not all students enrolled in the course completed both the pretest and posttest. A two-tailed *t*-test was used to compare the scores on the pretest and posttest (t (152)= -24.68, p =.000). Students' scores on the posttest (M=17.22 (4.84)) were significantly higher than they were on the pretest (M=9.10 (3.82)) indicating substantial gains in understanding of Newtonian mechanics. These gains (.41 std dev) are consistent with those that Hake found for several interactive-engagement courses in physics [32]. It is impossible to discern exactly what effects the analogical encoding treatments had on this gain. The improvement provides only evidence of improved conceptual understanding during the Newtonian portion of the course.

Model	Sum Squar	df	MeanSq	*F*	Sig.	R^2
Exam 1 Problem Solving - Regression	1012.63	1	1012.63	29.09	.000	.124
Exam 1 Problem Solving Residual	7135.53	205	34.81			
Exam 1 Conceptual - Regression	64.75	1	64.75	4.03	.046	.019
Exam 1 Conceptual - Residual	3292.02	205	16.06			
Exam 2 Problem Solving - Regression	746.77	1	746.77	18.76	.000	.087
Exam 2 Problem Solving	7363.59	185	39.80			

Residual						
Exam 2 Conceptual - Regression	64.50	1	64.50	2.51	.115	.008
Exam 2 Conceptual - Residual	4750.62	185	25.70			
Exam 3 Problem Solving - Regression	351.76	1	351.76	21.51	.000	.109
Exam 3 Problem Solving Residual	2877.83	176	16.35			
Exam 3 Conceptual - Regression	36.56	1	36.56	4.21	.041	.023
Exam 3 Conceptual - Residual	1525.57	176	8.67			

Table 3. Regression analyses assignments onto problem solving and conceptual understanding.

Discussion

An underlying assumption of this study was that any learning strategy, in order to have utility, must be able to be implemented in classroom settings. Despite the consistently positive findings for domain-neutral concepts, analogical encoding must be able to facilitate learning in authentic, classroom settings. However, conducting experimental research in classroom settings is subject to numerous limitations and a lack of experimental control. In this content, heavy course requirements precluded experimental manipulations of treatments and the high level of interpersonal interactions among students enrolled in the course precluded a control group or alternative treatment. In future studies, we hope to be able to implement more experimental control, although we anticipate confounding factors in the treatments.

Despite the methodological limitations, the results of this study provide preliminary evidence supporting the effectiveness of using questions to scaffold analogical encoding while learning to solve physics problems. In all five of the assignments, student scores on the analogical encoding treatment significantly predicted performance on examination performance. Additionally, the conceptual focus of the treatment to some degree facilitated significant gains on the Force Concept Inventory. We cautiously conclude that the analogical encoding can facilitate performance on more complex problems, such as those in physics.

The fact that conceptually oriented analysis of problems better supported traditional problem solving than conceptual understanding is a bit of a surprise, especially over the course of the semester. Such a result in a study with a shorter treatment period would have been less surprising These results contradict those of Hung and Jonassen [33] that showed that conceptually oriented strategies supported conceptual questions but not quantitative problem solving. In future studies, we will address this issue by using more standard forms for assessing schema quality (see discussion below).

Future Research

While this study demonstrates some effectiveness of analogical encoding on problem-solving performance and conceptual understanding in physics, numerous questions remain. In this study, we were constrained in the kinds of treatments we could implement because of pre-existing course requirements. In future research, we plan to address the following issues.

First, we need to compare the effects of questions scaffolded analogical comparison with no scaffold. Simply directing students to compare analogues has often proven insufficient for engaging structural comparisons. We plan to add an analogical encoding group that is not scaffolded by questions and compare it to. That is, present two problems and direct students to compare them (perhaps writing down their analysis). Compare that group with one or more groups that use questions to scaffold analogical encoding. If possible, compare with control group that does not compare problems.

Second, we plan to assess the relative effectiveness of providing feedback to students while they are completing their analogical comparison activities. Feedback is one of most well established methods for supporting learning, however, it is generally overly simplified. Hattie and Temperly [34] recommend that multiple kinds of feedback are required to provide learners about the nature of the task, how they are processing the task, how they can self-regulate so learners can answer questions, such as where am I going, how am I going, and where to next? It is likely that feedback on their conceptual comparisons will help students to induce stronger schemas that are more transferable.

We have found some support for the use of questions to focus the structure mapping process. Third, can these questions provide reasonable models for student question generation, and will student question generation facilitate schema induction and comprehension? Research has shown that teaching students how to generate questions about reading material improved comprehension [35]. The quality of student questions is a strong predictor of student achievement [36]. For example, King [37] found that when students were taught to generate questions that promote connections among ideas within a lesson as well as ones intended to access prior knowledge and experience engaged in more complex knowledge construction than those trained in lesson-based questioning. If students are able to apply models of structural mapping questions to problems, we predict that schema induction will improve. So, we plan to examine the effects of questions vs. no questions on question generation and then examine the quality of student-generated questions on schema quality and problem solving.

Fourth, we plan to explore different methods for assessing schema quality, including text editing [38, 39, 40] where students identify whether problems contain sufficient, irrelevant, or missing information; judging the similarity of problems [38, 39]; problem classification[8], or recall details of problems seen or solved previously [38] assuming that recall of surface detail poor schematic knowledge and recall of structural details indicates stronger schemas. These more precise measures of schema quality will more likely be related to problem-solving performance.

References

1. Cooper, G., and Sweller, J. (1987). Effects of schema acquisition and rule automation on mathematical problem solving. *Journal of Educational Psychology*, *79*, 347–362.
2. Sweller, J., and Cooper, G. A. (1985). The use of worked examples as a substitute for problem solving in learning algebra. *Cognition & Instruction, 2,* 59–89.
3. Rich, B. (1960). *Schaum's Principles of and Problems of Elementary Algebra*, Schaum's, New York.
4. Wilson, J.W., Fernandez,M.L., & Hadaway, N (n.d). *Mathematical problem solving*. Retrieved 9/22/05 from http://jwilson.coe.uga.
5. Lucangeli, D., Tressoldi, P. E., and Cendron, M. (1998). Cognitive and metacognitive abilities involved in the solution of mathematical word problems: Validation of a comprehensive model. *Contemporary Educational Psychology, 23,* 257–275.
6. Ploetzner, R., & Spada, H. (1998). Constructing quantitative problem representations on the basis of qualitative reasoning. *Interactive Learning Environments, 5*, 95-107.
7. Ploetzner, R., Fehse, E., Kneser, C., & Spada, H. (1999). Learning to relate qualitative and quantitative problem representations in a model-based setting for collaborative problem solving. *Journal of the Learning Sciences, 8*(2), 177-214.
8. Chi, M.T.H., Feltovich, .J., & Glaser, R. (1983). Categorization and representation of physics problems by experts and novices. *Cognitive Science, 5*, 121-152.
9. Dufresne, R.J., Gerace, W.J., Hardiman, P.T., & Mestre, J.P. (1992). Constraining novices to perform expertlike problem analysis: Effects on schema acquisition. *Journal of the Learning Sciences, 2* (3), 307-331.
10. Hardiman, P.T., Dufresne, R., & Mester, J.P. (1989). The relation between problem categorization and problem solving among experts and novices. *Memory & Cognition, 17*(5), 627-638.
11. Schoenfeld, A.H., & Herrmann, D.J. (1982). Problem perception and knowledge structurein expert and novice mathematical problem solvers. *Journal of Experimental Psychology: Learning, memory, & Cognition, 8*, 484-494.
12. Forbus, K.D., Gentner, D., & Law, K. (2002). MAC/FAC: A model of similarity-based retrieval. In. T.A. Polk & C.M. Seifert (Eds.), *Cognitive modeling* (pp. 911-940). Cambridge, MA: MIT Press.
13. Ross, B.H. (1984). Remindings and their effects in learning a cognitive skill. *Cognitive Psychology, 16*, 371-416.
14. Gentner, D. (1989). The mechanisms of analogical learning. In S. Vosniadou & A. Ortony(Eds.), *Similarity and analogical reasoning* (pp. 199-241). New York: Cambridge University Press.
15. Medin, D.L., & Ross, B.H. (1989). The specific character of abstract thought: Categorization problem solving, and induction. In R.J. Sternberg (Ed.), *Advances in the psychology of human intelligence* (Vol. 5, pp. 189-223). Hillsdale, NJ: Lawrence Erlbaum Associates.
16. Loewenstein, J., Thompson, L., & Gentner, D. (2003). Analogical learning in negotiation teams: Comparing cases promotes learning and transfer. *Academy of Management Learning and Education, 2* (2), 119-127.
17. Catrambone, R.., Holyoak, K. J. (1989). Overcoming contextual limitations on problem-solving transfer. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 15* (6), 1147-1156.

18. Gentner, D., & Markman, A.B. (1997). Structure mapping in analogy and similarity. *American Psychologist, 52* (1), 45-56.
19. Gentner, D., & Markman, A.B. (2005). Defining structural similarity. *Journal of Cognitive Science, 6*, 1-20.
20. Gick, M.L., & Holyoak, K.J. (1983). Schema induction and analogical transfer. *Cognitive Psychology, 15*, 1-38.
21. Cummins, D.D. (1992). Role of analogical reasoning in the induction of problem categories. *Journal of Experimental Psychology: Learning, Memory, & Cognition,* 18 (5), 1103-1124.
22. Gentner, D., Lowenstein, J., & Thompson, L. (2003). Learning and transfer: A general role for analogical encoding. *Journal of Educational Psychology, 95* (2), 393-405.
23. Spencer RM & Weisberg RW (1996). Context-dependent effects on analogical transfer. *Memory & Cognition, 14*, 442-449.
24. Kotovsky, L., & Gentner, D. (1996). Comparison and categorization in the development of relational similarity. *Child Development, 67*, 2797-22822.
25. Kolodner, J. L. (1997). Educational Implications of Analogy—A View from Case Based Reasoning, *The American Psychologist, 52*(1), 57-66.
26. Markman, A. & Gentner, D. (1993).Structural alignment during similarity comparisons. *Cognitive Psychology, 25*, 431-467.
27. Kurtz, K.J., Miao, C.H., & Gentner, D. (2001). Learning by analogical bootstrapping. *Journal of the Learning Sciences, 10* (4), 417-446.
28. Graesser, A.C., Baggett, W.& Williams, K. 1996). Question-driven explanatory reasoning. *Applied Cognitive Psychology, 10*, S17-S31.
29. Graesser, A.C., Swamer, S.S., Baggett, W.B., & Sell, M.A. (1996). New models of deep comprehension. In B.K. Britton & & A.C. Graesser (Eds.), *Models of understanding text.* Hillsdale, NJ: Lawrence Erlbaum Associates.
30. Eris, O. (2004). *Effective inquiry for innovative engineering design*. Boston: Kluwer Academic Publishers.
31. Hestenes, D., Wells, M., & Swackhamer, G. (1992). Force Concept Inventory. *The Physics Teacher, 30* (3), 141-151.
32. Hake, R.R. (1998). Interactive-engagement vsersus traditional methods: A six-thousand-student survey of mechanics test data for introductory physics. Am*erican Journal of Physics, 66* (1), 64-74.
33. Hung, W., & Jonassen, D.H. (2006). Conceptual understanding of causal reasoning in physics. *International Journal of Science Education, 28* (13), 1601-1621.
34. Hattie, J., & Temperly, H. (2007). The power of feedback. *Review of Educational Research, 77* (1), 81-112.
35. Rosenshine, B., Meister, C., & Chapman, S. (1996). Teaching students to generate questions: A review of the intervention studies. *Review of Educational Research, 66* (2), 181-221.
36. Graesser, A.C., & Person, N.K. (1994). Question asking during tutoring. *American Educational Research Journal, 31* (1), 104-137.
37. King, A. (1994). Guiding knowledge construction in the classroom: Effects of teaching children how to question and how to explain. *American Educational Research Journal, 31* (2), 338-368.
38. Low, R., & Over, R. (1989) Detection of missing and irrelevant information within algebraic story problems. *British Journal of Educational Psychology, 59*, 296-305.

39. Low, R., Over, R., Doolan, L., & Michell, S. (1994). Solution of algebraic word problems following training in identifying necessary and sufficient information within problems. *American Journal of Psychology, 107* (3), 423-439.
40. Ngu, B.H., Lowe, R., & Sweller, J. (2002). Text editing in chemistry instruction. *Instructional Science, 30*, 379-402.