# Cognitive Science: Problem Solving And Learning For Physics Education

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**Abstract.** Cognitive Science has focused on general principles of problem solving and learning that might be relevant for physics education research. This paper examines three selected issues that have relevance for the difficulty of transfer in problem solving domains: specialized systems of memory and reasoning, the importance of content in thinking, and a characterization of memory retrieval in problem solving. In addition, references to these issues are provided to allow the interested researcher entries to the literatures.

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## INTRODUCTION

To better conduct research on how people learn physics, we need a systematic approach to the principles of learning and a wide range of methods for examining this learning. Over the last thirty plus years, much research in cognitive science has examined these issues. The goal of this paper is to very selectively present a small portion of this work that may be of particular relevance to transfer in physics education and to provide entry references for both general approaches and specific issues. To begin the last aim, there are a large number of introductory textbooks that examine cognitive psychology and cognitive science [1,2], including from a more cognitive neuroscience perspective [3].

Although many cognitive science topics might be of interest to this community, I chose three that I thought might be less obvious and have implications for transfer: specialized systems, the importance of content in thinking, and the way in which memory retrieval during problem solving may lead to analogies, categories, and other problem-solving behaviors.

## SPECIALIZED SYSTEMS

It is common in education to mark out different types of knowledge and reasoning skills one wants the students to learn. The work in cognitive science has also considered a variety of knowledge and thinking types, so I present here some distinctions and how they might relate to transfer in physics learning. I focus on one distinction each in memory and reasoning that has important implications for this community. Different ways of representing and manipulating knowledge (i.e., memory and thinking) may have different operating principles that influence how people problem solve and learn.

### Memory and Reasoning Systems

Much research in cognitive science, neuroscience, and psychology has found that memory is not a monolithic entity but instead consists of a number (we do not know how many) of specialized systems that have different purposes and at least somewhat different means of representing and retrieving knowledge. A critical distinction for education is between procedural and declarative memory [4].

*Declarative memory* consists of factual information, "knowing that" information that relates single concepts. Examples include the memory of a worked-out problem, a formula, or a definition. These are quickly (although sometimes imperfectly) learned, can be flexibly accessed by different elements of the memory, and flexibly applied. For example, one can learn $f = ma$, access it given the word "acceleration" in a simple problem, and solve for $f$ or $m$ or $a$ given the other variables.

*Procedural memory* is "knowing how" to do something, a procedure. However, it is not the factual information of how the procedure is done (that would be declarative), but the actual processes to accomplish the procedure. For example, although we can tie a shoelace, most of us could not tell someone how we do it without watching (or imagining) ourselves tying the lace (parents who have taught this recently are the exception). The declarative knowledge we began with has been turned into a representation that can guide the tying but is no longer accessible in a verbalizable format.

The evidence for this distinction includes a large number of behavioral studies showing these lead to very different patterns of performance, of neuroscience studies showing differences in brain regions and amnesias, and computational models that are able to account for many different findings by using both types of representations [5-8].

Although reasoning theorists argue about whether the differences in reasoning require positing different systems, I think the evidence tends to favor those who see at least two different systems [9,10]. According to these views, System 1 is a heuristic processing system that works unconsciously in an associative manner, pulling to mind some use of knowledge that relates to the current information being processed. This processing is similar to some of the claims about how experts process situations, but also captures more simple associative reasoning in everyday thinking and in novices. System 2 is a more analytical, deliberative processing, such as one might see in a novice figuring out how to fill numbers of a problem into an equation. System 1 is usually thought of as a faster initial processing that provides an answer or passes information to System 2.

### Implications for Physics Learning

Why do these distinctions matter to you? As a simple motivation, I remind you of two observations that I am sure you have made. First, people often have the relevant knowledge but do not retrieve it at the time that it is needed [11]. Second, people who seem to be able to do one thing often cannot do something else for which the same knowledge is relevant. Although both of these observations can have multiple causes (e.g., age, intoxication, sleepiness), a common problem has to do with a mismatch of knowledge or reasoning processes. Thirty years ago, a principle of *transfer-appropriate processing* [12] proposed that performance depends not just on what you know and how you learned it, but on the similarity between the original processing and the way in which you are processing the information now. Because of the different memory and reasoning systems, the processing may differ enough from prior learning to lead to lack of transfer. Experimental studies show the importance of procedural overlap in predicting transfer [13,14] and the lack of full transfer when the same knowledge is learned and tested in different ways [15]. A common situation I had when teaching statistics to Psychology majors is that a failing student would express dismay since s/he had understood the way to solve the problem perfectly when I explained it in class. I had to point out that the exam did not test their understanding of my solution, but their ability to generate their own solution. This mismatch in processing is a common and underappreciated influence on transfer.

## CONTENT IN THINKING

Abstract thinking is hard. People usually think about specific people, things, situations, problems, etc. As educators we want them to learn the underlying abstract principles, but we underestimate the difficulty of abstract thinking probably because of our expertise in the domain and our interest in abstract principles. However, the extent and influence of specific (content-based) thinking may be much greater than we appreciate [16], both in novices and experts.

Novice physics students rely upon objects in problems when asked to sort problems by types [17]. However, the influence of superficial content information goes much further. A common practice in textbooks and classrooms is to present an abstract principle and then an example to illustrate the principle. We assume students use this example to refine exactly how the principle works, to clear up any ambiguities in what the words mean or how the formula might be applied. A more common result, unfortunately, is that students' understanding of the principle becomes intimately intertwined with the example used to illustrate it, so that details of that example are encoded as aspects of the principle [18-20]. In addition, although we might give multiple examples to avoid this overspecification of content and to allow the students to learn the intersection among the examples (i.e., the principle), they often still end up with knowledge that includes content [21,22]. Generalizations are often very conservative, partly because the novices do not know exactly which aspects are relevant and which are not. However, even when they do know that an aspect is irrelevant (such as the particular object), their declarative representation includes this information as they reason about the problem.

Why do they do this? One might argue that evolution has prepared us for dealing with the physical world and that very formal abstract principles are a much newer useful type of knowledge. Although I think this is true, it is also important to realize that even in formal domains, content is often correlated with the underlying structure, the principles. Given a problem is about an inclined plane, it is more likely to involve some principles than others.

Experts are also influenced by the content, although they may sort problems by underlying principles [23]. Given the correlation of content and structure in most domains and the relative ease of encoding content mentioned in the problem, the experts can at least use this predictive content to get a head start in accessing knowledge that is likely to be relevant. In algebra, the content and structure are so correlated that the names of many of the problem types are in terms of the content. For example, a usual "age problem" might be:

> Michelle is 4 times older than her niece. In 5 years, Michelle will be 3 times older than her niece. How old will they each be in 5 years?

However, one could also write the same underlying problem very differently:

> A mason mixed 4 times as much cement in one mixer as another. He added 5 liters of cement to each mixer. The first mixer now has 3 times as much cement. How much does each mixer have?

Although the problems have the same underlying solution, the content of the second is that typically found with "mixture" problems, so is unusual for this type of problem. Highly experienced algebra problem solvers were often misled by this unusual content when categorizing the problems and even had reduced solution accuracy for difficult problems. In addition, one algebra teacher showed the extent to which content is involved even with highly-learned problem schemas. When solving a problem from the river-current category (e.g., a boat goes downriver in t1 time and back upriver in t2 time, how fast is the current?) that substituted going back up a down escalator in a mall, she referred to the current of the escalator and going upstream. The schema variables include content because it makes it faster to map the problem variables to the schema variables. For domains in which content and structure are correlated (which is most domains), even experts will (and should) make use of it.

## CONSIDERING MEMORY RETRIEVAL

What people know and retrieve has a huge influence on their problem solving. I give a perspective on this issue that I hope will be helpful to this community in understanding the role of memory in problem solving and its relation to different problem solving such as equation-based, analogy, and the use of problem categories. A very simple view is that:

Cues → Memory → Retrieved Information → Problem Solving

That is, cues are used to probe memory, and the retrieved Information may either be used for problem solving or to reformulate the cues (for further memory retrievals). Even this simple view, supplemented with the principle that memory retrieval includes some similarity matching between the Cues and Memory, provides enough to understand some of the observed problem solving for novices and experts.

Novices begin with cues that consist of easily available aspects of the problem, such as objects and variables (e.g., if acceleration is mentioned they might use "variable a" as a cue) [17]. Their memory is likely to consist of some problems, such as worked-out examples, and many formulae. Given these cues and that memory, two results are most likely. One, they might retrieve an earlier example that matches the current problem in the objects involved. Two, they might retrieve a formula (or formulae) that contain one or more of the variables. The problem solving is thus likely to be by analogy to an earlier example or more equation-based, as they keep probing with known and goal variables for formula that might allow them to make progress towards the solution.

Experts' cues from reading the problem also include the objects, but some structure of the problem as well. Their memory consists of a much larger range of earlier problems, many formula, but also a variety of problem categories, with means for identifying the problem type and associated procedures for solving them (i.e., problem schemas) [17]. Given these cues and memory, they might retrieve analogies and formulae too, but the most probable outcome is to retrieve a problem category (both because the cue containing structure provides a strong match to the category in memory, plus the category has become a very available memory from much earlier use, as compared to any of the examples). Given this retrieval, one is likely to see a category-based (or principle-based) problem solution, perhaps falling back to analogies or equations for difficult or unusual problems.

I am not trying to present a full theory of how memory is used in problem solving, but just enough to point out what I hope will be some useful points. First, the type of problem solving observed can often be understood in terms of the memory and cues. Second, analogy and category-based problem solving are similar in many ways. Early abstractions often arise from using analogies [18,24,25] and problem categories may arise with much more practice with these generalizations [26].

This is a very simplified picture, but I do want to mention two important other influences. First, the cues are not the problem elements, but the problem as interpreted by the problem solver [27]. This representation of the problem is critical and has huge influences on problem solving [28] at least partly due to what knowledge is retrieved. Second, novices might be able to improve their problem solving by learning to do some more structural analysis and storing the results in memory (to be accessed by cues for later problems), such as with self-explanations [29,30] and strategy-writing [31].

## CONCLUSIONS

Cognitive science may have some useful principles and methods for researchers interested in physics education. In this paper, three issues are discussed (specialized systems, content in thinking, and memory retrieval in problem solving) and references are provided to permit entry to the relevant literatures.

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