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Perceptual Learning Modules in Mathematics and Science Instruction

Joseph A. Wise, *W. M. Keck Math/Science Institute, Crossroads School*
Tate Kubose, *University of California at Los Angeles*
Norma Chang, *W. M. Keck Math/Science Institute, Crossroads School*
Arlene Russell, *University of California at Los Angeles*
Philip J. Kellman, *University of California at Los Angeles*

Abstract

Research in cognitive science suggests that perceptual learning -- changes in information extraction leading to efficient detection and classification of relevant pattern structure – is a crucial component of expertise in many domains, including mathematics and science. Traditional learning formats do not do much to develop discovery or automaticity in the processing of structure, but appropriate conditions for doing so can be achieved using computer-based educational technology, in the form of Perceptual Learning Modules (PLM's™). Here we report progress in three domains using PLM's: university organic chemistry, multiple representations (graphs, equations and word problems) of linear functions and algebraic equivalences. These projects are in different stages of implementation, but objective data collected in two of them strongly support the value of PLM's in secondary school and university mathematics and science instruction.

1. INTRODUCTION

Educators should subject new technologies, along with older instructional practices, to two obvious questions: 1) What are our goals for what students should know and be able to do? and 2) What procedures can accomplish those goals? Especially in mathematics and science, most instructional settings get at least part of the answers to both questions wrong.

One common goal of instruction expects that learning in a given domain consists of stating facts and concepts, what cognitive scientists call *declarative knowledge*. Limitations on this idea are seen in the student who can state the concepts or facts, but fails to correctly apply them to solving a new problem. We encounter the limitation again when experts classify or solve problems, yet cannot convey their insight in how they solved the problem to another person.

Learning and expertise involve other dimensions besides declarative knowledge. Specifically, they involve changes in the ability to detect and classify patterns and structure in a given learning domain [1, 2, 3]. In a classic book, Gibson labeled these abilities *perceptual learning* [1]. The human attentional system seems geared to grow in its ability to isolate relevant detail, suppress irrelevancy and pick up progressively deeper structure, as a result of appropriate kinds of learning experiences. The ability to see patterns can grow to astonishing levels of sophistication, and it is a cornerstone of advanced performance in many domains, such as science and mathematics, chess, aviation, radiology, and others [2].

As our knowledge of the role of perceptual learning increases, it becomes clearer that classroom procedures must account for and nurture students' natural tendency for perceptual learning. The idea that perceptual learning of complex structure is a natural consequence of certain kinds of learning experiences may come as a shock to teachers. After all, year after year, many students seem resistant to absorbing even the basics of scientific or mathematical concepts, and even fewer can apply these productively in problem solving. Students continue to struggle with distinguishing relevant and irrelevant information and in mapping appropriately across representational formats. These difficulties are hard to understand from the standpoint of traditional instruction. Teachers often assume that if a lecture has been delivered clearly, or if an example or two has been worked in detail, an attentive, earnest student should absorb the relevant concepts.

From the standpoint of theory and research in perceptual learning, however, the difficulties are not only understandable, they are expected. A given presentation of a concept contains a wealth of information, some relevant and some irrelevant. We may tend to forget that this is true as well of the representations we use. A graph of a function for example, contains crucial information in terms of the shape of the function, intercepts, scaling, and so on. The student does not intuit immediately what are the relevant and irrelevant features of the representation. The slope and intercept of a linear function, known by the instructor to be crucial, may not "jump out" at the student any more than the color of the chalk.

Basic research carried out over the past few decades suggests that there are classroom procedures that directly address this neglected, but crucial, dimension of learning. Moreover, the requirements for perceptual learning are perfectly suited to being implemented in modern, computer-based instruction. In laboratory experiments, certain learning conditions lead to orders of magnitude improvement in extraction of task-relevant detail [4] and unconscious extraction of complex pattern structure [2, 5, 6, 7]. These conditions also change pattern extraction from an effortful, attention-consuming process to an automatic one [8].

Effective classroom procedures should incorporate *discovery* and *automaticity* [9]. Discovery in the learning of structure is a process of filtering which of the possible details, patterns, and relationships are relevant to a particular goal or task. Although there is some benefit to having relevant features pointed out explicitly, humans possess a basic learning process that progressively isolates the relevant features and directs attention toward them, while suppressing attention to irrelevancies [1]. This learning process advances when the subject makes rapid classifications and receives feedback over many short trials [11]. A large number of trials allows differentiation between relevant and irrelevant information, and leads to discovery of larger patterns and relationships [1, 12].

The same conditions – active classification over many short, rapid trials – allows another change in information processing to occur. This is termed automaticity [13]. Practice in information pick-up allows the same processing to occur with progressively smaller allocation of attention or effort. The student who has mastered a mathematical or scientific concept only at the level of memorized declarative knowledge may need substantial effort to apply it in problem solving. The value of automaticity is that if basic pattern recognition becomes automatic, attention and effort are left for dealing with higher-order aspects of the problem. Perceptual learning modules™ (PLM's) can make such basic concepts and patterns intuitive and therefore less demanding of attention [9].

Moreover, these procedures allow for continuous monitoring of objective performance, e.g., students' accuracy and speed at relevant structure classification tasks. The need for objective data in evaluating instructional methods is crucial, yet often omitted in favor of either subjective student acceptance ratings (or no data at all). PLM's provide online assessment of student progress, allow learning to proceed to set criteria, and readily support objective tests of transfer to other tasks [3].

In what follows, we describe three examples of PLM's in various stages of implementation and data collection. One project addresses students' mapping between multiple representations in the analysis of scientific problems involving linear functions. A second project addresses university-level students' intuiting of molecular structure and patterns in organic chemistry. A third project addresses students' facility with algebraic equivalences. These projects are collaborative efforts of members of the UCLA LIS (Learning and Intelligent Systems) Group, the UCLA Molecular Science Project and the W. M. Keck Math/Science Institute at Crossroads School.

2. THREE PLM EXAMPLES

2.1 Linear Functions PLM

In this study, we attempted to apply the ideas to multiple representations of linear functions as they appear in the high school physical science curriculum. Linear functions are a cornerstone of work at this level, appearing in time, distance, and velocity problems in physics, and rate problems in chemistry. Three kinds of representations are important in dealing with these problems: algebraic expressions or equations, graphical representations and word problems. Each of these representational formats has advantages in making certain kinds of information explicit, but each also carries heavy burdens in terms of students' learning to grasp the important details and structures in each. Moreover, the mapping between these representations is a notoriously difficult hurdle of science and mathematics education. Our goal was to improve students' abilities to perform mappings across the problem representations to facilitate the use of each and their combined employment in thinking and problem solving.

Method. We developed a PLM involving rapid classification of the sort that has previously proven effective in perceptual learning [3, 11]. We aimed to increase the efficiency and accuracy of mapping across multiple representations (visual, symbolic, linguistic) of the same problem.

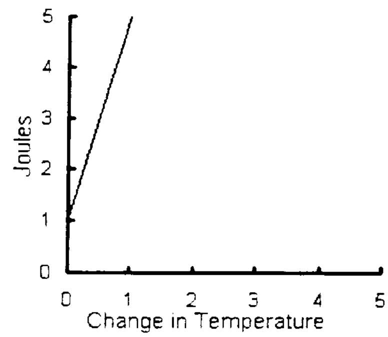
Each trial in the module involved the presentation of one representation of the problem and required the learner to choose the correct match of a different representation from among three choices. Note that this PLM did not ask students to solve the problems presented, but rather to match the different representations of problem information. For example, a word problem might be presented, followed by three graphs, from which the subject would choose one. The target was presented for 2 seconds. The choices were presented until a response was entered. Feedback (correct or incorrect) was presented for up to ten seconds. An example of a word problem was:

> An object starts with 1 joule of heat. It gains 4 joules of heat for every 1 degree Celsius change in temperature. How many joules of heat would it contain if the room temperature increased 3 degrees Celsius?

The corresponding equation for this problem would be:

$$y = 4x + 1$$

The graph for this problem would be as shown below:



There were six different trial types; subjects received a mixture of all 6 during the learning phase. The six problem types were:

	Target Representation	**Choice Representation**
1	Equation	Graph
2	Equation	Word Problem
3	Graph	Equation
4	Graph	Word Problem
5	Word Problem	Equation
6	Word Problem	Graph

Predictions. We predicted that the PLM should: 1) increase performance as measured by increased response accuracy and reduced reaction time,
2) produce accurate near transfer as measured by the high performance on novel problems, and 3) produce remote transfer as measured by the improvement on post test items designed to assess the learner's understanding of the structure of linear word problems. A more remote transfer test, in which subjects are scored for actually solving these problems, is currently in progress in a separate experiment.

Results and Discussion. The training module was successful in increasing performance and producing accurate near transfer. Figure 1 below shows that accuracy increased reliably during the learning phase and was actually slightly better for novel problems in the transfer test. Meanwhile, response times dropped dramatically, as shown in Figure 2.

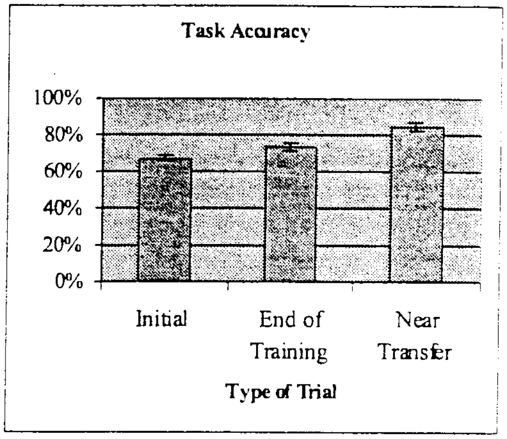


Fig. 1

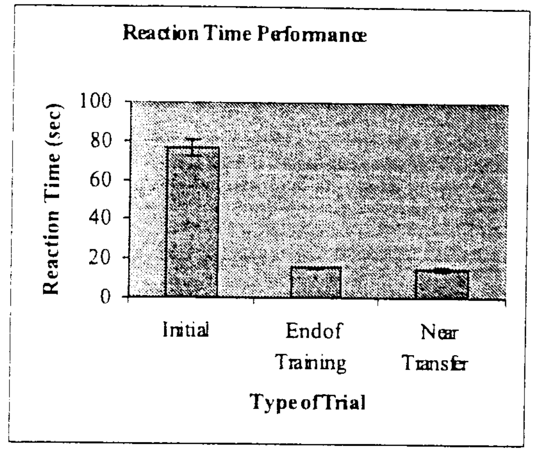


Fig. 2

Whereas in the first trial block (ten problems), students required an average of 80 seconds to do each problem, by the end of training, the relevant mappings were made in about 15 seconds, a decrease of nearly 80% in the time required to grasp the relevant structure. Moreover, this dramatic gain in speed (suggesting more automatic pattern processing) held for novel problems in the transfer test. Although the module did not produce any increase in conceptual knowledge by our measurement, we are currently evaluating a more suitable remote transfer test, which assesses transfer to actual solutions of word problems. The Linear Functions PLM required only one 55-minute period of learning time, yet led to substantial gains in students' abilities to extract the structural similarities between different representations of the same problem and an impressive degree of improvement in the speed of processing.

2.2 Three-Dimensional Angles PLM

A notorious problem in the first term of university-level organic chemistry is that students do not perceive the three-dimensional structure of molecules from two-dimensional representations they are given, despite the careful and extensive coverage of the topic in lecture, in discussion sections, in homework, on exams, and in the use of molecular models. Using research on perceptual learning, we developed PLM's to teach this difficult concept. A controlled study of student understanding of three-dimensional structure was conducted at UCLA during summer 1999.

Method. The control class received traditional instruction. The instruction with the treatment class was followed by practice using the *3-D Angles PLM.* In *3-D Angles*, a rotating, 3-D model of a molecule is presented on a computer monitor on each trial. Subjects are queried about one of three aspects: Either 1) an atom is highlighted and the number of bonds (coordination number) it forms in the molecule must be indicated, or 2) two bonds involving the same atom are highlighted and subjects must indicate (from 4 choices) the correct geometric angle between the bonds, or 3) students must indicate for a given atom its hybridization from among 4 choices. All responses are scored for speed and accuracy and feedback is given after each trial, as well as cumulatively after each block of ten trials. The learning phase ten blocks of ten trials each) took less than half an hour.

Results and Discussion. Students using the PLM improved substantially in making rapid classifications about molecular structure. All reached nearly perfect levels in classifying coordination number, bond angle and hybridization of a large variety of compounds. These abilities transferred readily to new examples (near transfer). Most interesting, this modest amount of training produced significant gains in students' abilities to correctly perceive the structural features of molecules, even when the most impoverished representations were given to them. On the course final exam, students were presented with planar, line-and-letter representations of molecules and asked to indicate bond angles (Table 1) or hybridization (Table 2). Control subjects who received lecture information only resembled the experimental treatment group's pretest performance in both cases: Both groups made high percentages of incorrect responses for bond angle and hybridization. After the 3-D Angles PLM, however, accuracies improved reliably for a number of the test molecules. (A full report of this research is in preparation for publication elsewhere [14].)

The results indicate that educational technology using perceptual learning concepts can successfully lead to the learning of structure, and that this learning can transfer to a meaningful task in chemistry, one that is demonstrably resistant to conventional instructional methods.

Table 1 Bond Angle Identification When Presented with Impoverished Representation. (From Russell & Kellman, in preparation)

	% Incorrect		
	control	Treatment	
	lecture only	after lecture	After *3-D Angles*
	final	pretest	Final
H_2O (O)	42.3	42.4	11.9 **
CO_2 (C)	11.5	5.1	5.1
Cycloalkane(line structure only) (C)	42.3	52.5	20.3 **
Carbonyl (C)	15.4	20.3	8.5
Alkene (C)	7.7 *	22.0	5.1 **
Amine (N)	46.2	47.5	20.3 **

*, ** significant differences $P < 0.01$

Table 2 Hybridization Identification When Presented with Impoverished Representation. (From Russell & Kellman, in preparation)

	% Incorrect		
	control	treatment	
	lecture only	after lecture	after *3-D-Angles*
	final	pretest	final
Primary alcohol (O)	22.3 *	44.1	35.6
HCN (C)	3.9	18.7	5.1
Benzene (line structure only) (C)	0 *	20.4	5.1 **
Carbonyl (C)	3.9	10.2	1.7
Alkane (C)	7.7	13.6	11.9
Amine (N)	34.6	57.6	39.0

*, ** significant differences $p < 0.01$

2.3 Algebraic Equivalences PLM

As in the two domains discussed so far, the importance of conceptual understanding in learning algebra is usually well emphasized. Many problems in learning algebra, however, may relate to the lesser emphasis in instruction on developing pattern recognition and transformation skills. The problems are evident in students' mistakes. Teachers of high school math and science often find students who can explain the meaning communicated by an algebraic statement such as $4x - 3 = 12$ but who will habitually try to solve for x in that statement by subtracting 4 or dividing by 3. Their interpretation of the symbols' meaning is accurate but too slow to engage, allowing competing processes in their brains to tackle the problem incorrectly. The misapplications that result from these shortcuts suggest that students are relying on half-remembered patterns absorbed during class. To them, the surface similarities between the solutions illustrated below may be more immediately evident than the conceptual conflicts between them:

$$\begin{array}{c} \dfrac{\cancel{4}x}{\cancel{4}} = \dfrac{12}{4} \\ x = 3 \end{array} \quad vs. \quad \begin{array}{r} \cancel{4}x = 12 \\ -\cancel{4} \quad -4 \\ \hline x = 8 \end{array}$$

Fig. 3

$$\begin{array}{r} x + \cancel{4} = 8 \\ -\cancel{4} \quad -4 \\ \hline x \quad = 4 \end{array} \quad vs. \quad \begin{array}{c} \dfrac{x + \cancel{4}}{\cancel{4}} = \dfrac{8}{4} \\ x \quad = 2 \end{array}$$

Fig. 4

$$\begin{array}{r} 2x + 3 + 5x - 4 = 11 \\ -3 \qquad\qquad -3 \\ \hline 2x \quad + 5x - 4 = 8 \end{array} \quad vs. \quad \begin{array}{r} 2x + 3 + 5x - 4 = 11 \\ -3 \qquad -3 \\ \hline 2x \quad + 5x - 7 = 11 \end{array}$$

Fig. 5

These common mistakes illustrate the potency of the perceptual aspects of learning. Not only do students fail to extract the correct structural relations, but they also fall prey to superficial resemblances among expressions which lead to error. Preventing the acquisition of incorrect patterns, increasing students' grasp of relevant structural relations, and improving their facility with algebraic manipulation are all key goals that are not optimally addressed by conventional instruction. To this end, we have designed a PLM for algebraic equivalences. A key assumption of the module is that students will benefit from comparisons of correct and incorrect answers that occur close together [15, 16].

Method. On each trial in the module, an expression (the target) is presented on a computer monitor. Below, several other expressions (the choices) are also presented. The student's task is to select all and only the choices that are equivalent to the target. Unlike the PLMs described earlier, this module allows for multiple correct answers, since solving real algebra problems requires choosing the most useful equivalence from infinite possibilities. (For example, too often, when students solve for x in the example, we see rote application of the distributive property, rather than the much simpler division by 7.) Our goal is not to promote default algorithms, but to expand students' library of possible strategies to facilitate adaptable problem solving.

Another important consideration for this module was building in the flexibility of randomly generated problems. Although the specific operations shown in each algebraic representation had to be hard-coded into the program, we wanted to reinforce the concept of variables by literally allowing them to vary. In the future, we may seek to expand this capability by substituting in expressions such as, rather than just integer values, for each variable in a given template.

Implications. Although we have not yet begun data collection on this PLM, we present it as an example of the sort of problem in mathematics and science learning that may be perfectly suited to computer-based educational technology combined with perceptual learning concepts. We have high hopes for this module in particular and for this approach in general to improving teaching and learning.

3. CONCLUSIONS

These efforts to apply perceptual learning to mathematics and science education have several features in common. They all address aspects of learning that are considered difficult or resistant to traditional instruction. In each case, they aim to help students discover and fluently process important patterns and structures, and in two cases, to map these structures across very different representational formats.

Our data suggest another commonality. In the two cases for which results are available, and in other research [3], the modules appear to confer substantial benefits, despite being used by students for very modest amounts of time. More research is needed, both to optimize the design and impact of PLM's, as well as to determine how best to integrate this new learning format with existing ones.

A final common theme in our PLM's for science and mathematics learning is that they suggest that perceptual learning principles and computer-based educational technology form a nearly perfect marriage. The capabilities for presenting large numbers of displays, collecting rapid responses and giving quick feedback are important in engaging cognitive processes that discover relevant structure amidst irrelevant detail. Likewise, the capacities to monitor performance objectively, and in the future to adapt the learning to the level and needs of each learner, are relatively new opportunities made possible by digital technology. These opportunities will only increase with the advent of better multimedia and virtual reality technology. The evidence suggests that implementing perceptual learning concepts will be a key means of extracting from this emerging and evolving technology genuine advances in teaching and learning.

Footnotes

Perceptual Learning Modules™ is a trademark of Kellman A.C.T. Services, Inc.

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