Using a computer simulation to compare expert/novice problem-solving subroutines

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Abstract:
Hierarchical problem-solving strategies employed in solving exercise science problems were examined in this study, which also tested the validity of an educational computer simulation. Hypothesis testing was used as the theoretical base for the study of differences in problem-solving within the computer simulation. In a previous study two groups of undergraduate (novices) and graduate students were compared in their ability to solve exercise science problems. The present study added a group of faculty (experts) who were presented with the same simulation protocol as the other subjects. Protocol analysis and the Pitt coding system were used to analyse verbal data. Group differences were examined statistically. The faculty were superior in interpreting data and used the Basic Heuristic and Pattern Extraction strategies for the generation and use of algorithms. The problem-solving strategies varied for each group based on the perceived difficulty of the problem, the knowledge base available, and the similarity of the given problem to previous problems.

Article:
The superiority of experts over novices in their ability to solve problems seems, on the surface, to be merely an expectation based on common sense. An expert can solve a problem faster and more accurately than a novice; however, of greater interest are the rules and strategies employed by the expert compared with those of the novice. The validity of a computer simulation rests not merely on the fact that novices and experts differ. Knowledge of *how* they differ in ability is essential. Ability differences are often evident in the strategies or heuristics used to solve problems. Knowledge of the differences in expert and novice problem-solving strategies can enhance the learning of novices by identifying and teaching expert schemata as a component of knowledge. The schemata integrate theoretical and experimental knowledge to create effective diagnostic, prescriptive, and educational problem-solving strategies. Information processing models have been used to characterise adult processing of well-defined problems having a specifiable knowledge base.

Some of the earlier research on ability differences in problem-solving of novices and experts compared master chess players with lower level competitors. Chase and Simon (1973) reported a simple experiment in which 25 pieces were positioned on the chess board as they might be in an actual game. The board was shown to chess players for 5 to 10 seconds; then the player was asked to reproduce the pieces in the same position from memory. The master could carry out this task with 90% accuracy, while the novice player could at best reposition 5 or 6 pieces accurately. When the same 25 pieces were positioned randomly on the board, neither the master nor the novice could accurately replace more than 5 or 6 pieces '. . . these perceptual skills stem from no innate general superiority of memory, or capacity to visualise, for the superiority is limited strictly to the expert's area of competence—only typical situations are retained' (Larkin *et al* 1980, 1338). Simon and Simon (1978) explored differences between experts and novices in their ability to solve simple physics problems. The experts displayed superiority in a number of respects, including the use of longer leaps in the problem-solving process as opposed to a step-by-step process and a working-forward strategy rather than a working-backward strategy. Pitt (1983) used a model of problem-solving incorporating both information processing and Piagetian paradigms in studying the ability to solve elementary chemistry problems. Although her study was developmental in nature rather than a comparison of novice-expert abilities, the model is directly applicable to a study of the problem-solving abilities of novices and experts.

The examination of solution strategies selected by problem-solvers is important in understanding the progressive development of ability. When initially confronted with a problem, novice problem solvers are more likely to use an information processing theory, such as a means-end analysis (Newell and Simon 1972). When using a means-end analysis, they tend to focus attention on the goal and work backwards toward the problem statement. Although this strategy is technically efficient, especially if the goal is simple and clearly stated, it may not lead to the development of expertise.

A more fruitful approach to problem-solving is hypothesis testing theory (Levine 1975) in which a series of hypotheses relevant to a particular category of problems under examination are tested (Chi *et al* 1981; Murphy and Medlin 1985). Problems are categorised based on a set of principles or rules, activating knowledge structures or schema necessary for success. Problem-solving ability under hypothesis testing theory is enhanced as the individual's knowledge base and experience with a particular type of problem increases (Larkin *et al* 1980).

In a previous study (Ennis and Safrit, in press), hypothesis testing theory was used as the theoretical foundation for designing a computer simulation that promotes increasingly sophisticated tactics in problem-solving in exercise science. The Health and Fitness Assessment (HAFA) computer simulation (Safrit *et al* 1988) was used to examine the extent to which undergraduate and graduate students used hypothesis testing theory when assessing fitness data and developing exercise prescriptions. Simulated problem-solving permits the subject to synthesise professional knowledge in clinical situations. The Pitt (1983) problem-solving coding system was used to organize the responses into heuristic and strategic problem-solving processes. The subroutines identified under these processes represented six problem-solving strategies. The graduate and undergraduate students were significantly different on only the general problem solver strategy, representing the means-end algorithm for achieving consecutive subgoals. Graduates had 75% more responses fitting this strategy. The strategy was used most often when the graduate student responded incorrectly. The subject diverted from hypothesis testing to a means-end strategy to evaluate the solution chain methodically.

However, group differences did exist within strategies. The graduates *were* superior in the ability to select evaluative criteria, edit algorithms, and list relevant and delete irrelevant information. Although graduates and undergraduates were similar in their ability to list assumptions and assign priorities, undergraduates tended to guess more often, thus limiting the accuracy of their responses. Graduates were better than undergraduates in listing possible questions, identifying algorithms, and executing the program, although there were no differences detected in the ability of the two groups to list given information and select relevant questions—both low level processes. Graduates and undergraduates could also formulate hypotheses, define predictors, and match data to predictions. Graduates, however, could more accurately determine the truth value of predictions.

Both undergraduates and graduates used all six strategies, but graduates frequently provided a significantly greater number of responses within many of the subroutines of the strategies. Graduate students were better able to evaluate the problem and were more adept at the problem-solving process than undergraduates. However, while the undergraduate students were clearly novices, the graduate students could not be considered experts. Although their knowledge base exceeded that of the undergraduates, most of these students had little experience in applying this knowledge in clinical settings. Specifically, graduates were unable to incorporate advanced level subroutines such as matching data to predictions, extracting patterns from data, summarising relevant patterns, and developing conclusions. Thus, this study was undertaken to examine the responses of experts as they interacted with the computer and to compare the differences in problem-solving ability of true experts to those of graduates and undergraduates.

Method

Subjects

In the Ennis and Safrit study (in press), 6 undergraduate and 7 graduate students were compared in their ability to solve fitness problems using a computer simulation. The present study added a group of 6 faculty in exercise physiology who were presented the same simulation protocol the other subject pools had received. The faculty members were considered to be experts in their knowledge of physiology as it applies to exercise. All had PhD degrees in exercise physiology and were professors in a large university in the United States.

Description of the computer simulation

The Health and Fitness Assessment program (HAFA) is a computer simulation used to solve problems associated with the assessment of fitness status and the generation of exercise prescriptions (Safrit *et al* 1988). The HAFA program gives the student two problem-solving options, interpreting data for either a hypothetical case study or a real subject. The variables are physiological and fitness parameters that describe the subject's fitness status. After analysing the data for a subject, the student is then asked to design an exercise prescription for this subject. The student is then asked to assume that the subject has followed the prescription for six weeks. New data are then presented for the student to analyse. The prescription is modified if warranted by the new data. Two types of feedback (Cohen 1985) are used in the simulation. One type is knowledge of results, whether the student selects the right or wrong response to a problem. The second type is informational feedback that allows the learner to correct an error by providing sufficient information. A Help menu can be used to review relevant tutorials and tables of norms.

The development of the HAFA program began in 1986. It was written in *C* language, utilising an IBM PC C Compiler along with Assembly language for some of the subroutines. A Toolkit program was used to assist in developing the graphics. Computers within the project were configured in a token ring network with an IBM PC-AT serving as a host computer.

Pitt problem-solving coding system

Pitt (1983) proposed a coding system that encompasses a variety of strategies used in problem solving. Twenty-four subroutines, listed in Table 1, are organised hierarchically into heuristics and strategies. The categories range from basic components of problem-solving such as recall or listing of given information (SRI) to the more complex subroutines involved in extracting patterns (SR22), summarising patterns (SR23), and drawing conclusions (SR24). Heuristics represent a theoretical hierarchy of subroutines that facilitate problem definition (SR1-9), data acquisition (SR10-19), and data interpretation (SR20-24). Subroutines are further organised into six strategies that appear to expedite the problem-solving process.

The six strategies in the Pitt coding system, listed in the right column of Table 1, provide a detailed representation of the problem-solving strategies. The Basic Heuristic and the General Problem Solver strategies are described by lower level subroutines in the hierarchy. The seven subroutines within the Basic Heuristic strategy form the scaffolding for the problem solving process. The most elementary subroutine, list given information (SR 1), serves as an entry point to orient the problem-solver to the problem. This is followed by two subroutines (SR3, SR9) which focus the process on critical questioning. Subroutines to list possible questions (SR3) and select questions (SR9) document the subject's efforts to identify productive avenues for examination. Once focused, the problem solver uses a second pair of subroutines to search for available algorithms (SR 13) and select the most appropriate algorithms (SR 14) for effective solution. The remainder of the Basic Heuristic is concerned with the execution of the solution or program (SR16) and output of conclusions (SR24).

The General Problem Solver strategy is a hierarchically more sophisticated strategy than the Basic Heuristic and is used to summarise the problem-solver's progress to that point in the solution process. It is a means-ends assessment of the progress to date, and includes a re-examination of the goal and the problem statement in an attempt to diminish the distance between the two. General Problem Solver subroutines (SR10, SR11, SR12) assist the problem solver to evaluate the known information and identify additional data needed for the next response. The strategy begins by defining the initial problem state (SR10) followed by a mental review of the final goal (SR 11). It terminates with an identification of the data needed (SR12) to diminish the remaining distance between the goal and the problem state.

Table 1: Components of the model: subroutines (SRs) grouped as heuristic subprocesses and strategies

Heuristic subprocesses	*Strategies*
Definition of the problem	General problem solver (GPS)
SR1. List given information	SR10. Define initial state
SR2. List assumptions	SR11. Define goal state
SR3. List possible questions	SR12. Identify data needed
SR4. Select evaluative criteria	
SR5. Assign priorities	Feedback
SR6. List relevant information/ delete irrelevant information	SR17. Identify feedback SR18. Tag new information SR19. Organise data
SR7. Formulate hypotheses	
SR8. Define predictions	Pattern extraction
SR9. Select question(s)	SR22. Extract patterns from data
	SR23. Summarise relevant patterns
Data acquisition	
SR10. Define initial state	Hypothetico-deductive
SR11. Define goal state	SR7. Formulate hypotheses
SR12. Identify data needed	SR8. Define predictions
SR13. Identify set of available algorithms	SR20. Match data to predictions
	SR21. Determine truth values of prediction
SR14. Select algorithm	
SR15. Edit algorithm	
SR16. Execute program	Evaluation
SR17. Identify feedback	SR2. List assumptions
SR18. Tag new information	SR4. Select evaluative criteria
SR19. Organise data	SR5. Assign priorities
	SR6. List relevant information/ delete irrelevant information
Interpretation	
SR20. Match data to predictions	
SR21. Determine truth values of predictions	SR15. Edit algorithm
SR22. Extract patterns from data	Basic heuristic category
SR23. Summarise relevant patterns	SR1. List given information
SR24. Output conclusions	SR3. List possible questions
	SR9. Select question(s)
	SR13. Identify set of available algorithms
	SR14. Select algorithm
	SR16. Execute program
	SR24. Output conclusions

Reproduced from Pitt, R B (1983). Development of a general problem-solving schema in adolescence and early adulthood. *Journal of Experimental Psychology: General, 112*(4), 552, By permission.

Within the Pitt system, hypothesis testing strategies associated with forward-chaining are evident in the Evaluation and the Hypothetico-Deductive strategies. Consistent with the goals of hypothesis testing, the Evaluation strategy includes subroutines that focus or delimit the domain. Problem solvers begin by identifying the assumptions stated or deduced from the problem statement (SR2). Then, based on previous knowledge or experience, they select criteria that serve as the basis for the evaluation (SR4). Criteria are prioritised based on relevance to the given problem (SR5). The efficacy of the selected criteria determine the extent to which the problem solver will be able to identify relevant and irrelevant information in the given statement (SR6). The ability to discriminate among the criteria at this stage of the evaluation process is instrumental in the implicit editing of the developing algorithm (SR15).

The Hypothetico-Deductive strategy involves the statement and testing of hypotheses. It emphasises the knowledge and experience necessary to formulate and test hypotheses within a specific domain. The problem-solver frequently begins with a statement of the knowledge base on which the hypothesis rests (SR7). This is followed by an attempt to define the parameters of the prediction (SR8). At the most sophisticated levels of hypothesis deduction, problem-solvers try to match the data given in the problem statement with their prediction (SR20), thus providing the basis to determine the truth value of their predictions (SR21).

The Feedback and the Pattern Extraction strategies focus on the integration of new knowledge and generation of rules or principles essential for transfer. In the Feedback strategy, the problem-solver consciously identifies (SRI 7) and integrates new information (SR18) not given in the problem statement. This information may take the form of theoretical knowledge or practical application. The most critical aspect of this strategy is the synthesis of the given data with a supplemental knowledge base. As the synthesis progresses, problem-solvers reorient their thinking to accommodate the evolving solution. The Pattern Extraction strategy includes subroutines to extract patterns from the data (SR22) and summarise relevant patterns (SR23) for future use. Central to the approach is the identification of patterns that serve as internal cues to the advanced problem-solver. Instead of arbitrarily selecting hypotheses based on knowledge and experience as in the forward-chaining strategy, the problem solver selectively analyses patterns that have evolved in the process of examining several subgoals or problems. Thus the history of previous interactions, including a *knowledge* of the particular category of problems and the *order* in which the problems have been presented, has a substantial impact on problem solution. The rule induction strategies employed at this level of problem solving facilitate knowledge transfer, encouraging a dynamic, internally-controlled learning process characteristic of expert problem solvers (Klayman and Ha 1989).

Protocol

The subject was seated at the computer and asked to talk continuously while interacting with the simulation. The investigator used probes throughout the session to encourage the respondent to explain the rationale underlying the decision. The subject was not permitted to answer a question by pressing a key until the rationale for the response was presented. Examples of probes used by the investigator were: (a) What information are you going to use to answer this question? (b) Describe the thinking process you are using to decide on the answer. (c) Can you state any rules or principles that are useful to this question? At specific points in the program, the subject was asked to summarise information and identify problems that might have occurred in the decision-making process. All responses were recorded and transcribed for analysis. Results from this procedure should be interpreted cautiously because subjects' perceived problem-solving may not always coincide with the actual problem-solving strategies.

Data analysis

Protocol analysis, a procedure developed by Ericsson and Simon (1984) to analyse verbal data, incorporates an information processing model as the basis for encoding verbal protocols in an explicit and objective manner. The written transcript was first pre-processed to identify relevant data. The statements were placed in protocol format, with each statement identified by the subject's initials and the statement number. Subroutine numbers reflecting the Pitt (1983) coding system were then identified for each statement.

Constant comparison analysis (Glaser and Strauss 1967) was used to further categorise the subroutine data. Constant comparison is an inductive process that provides a systematic procedure for classifying qualitative data. This two-part process involves both scanning and comparing protocol statements to detect embedded commonalities. Properties for each subroutine were used to further classify the statements. Rules were generated and each statement was tested and compared with the rule to determine category membership. The rules were then refined to the extent that each category was mutually exclusive. Subcategories and rules emerged from the subjects' thought processes as reflected in the protocol statements rather than being imposed through an external categorisation system.

The data analyses consisted of group comparisons using chi square tests, repeated measures analyses, and t-tests where appropriate. Experiment-wise error rate was controlled using the Bonferoni procedure. Post-hoc analyses were conducted when significant group differences were detected. The reliability of the coders was estimated.

Table 2: Summary of responses

Level	Subroutine	Undergraduate	Graduate	Faculty	Total
I	1	19	23	149	191
	2	85	113	13	211
	3	50	67	51	168
	4	316	513	93	922
	5	481	613	125	1119
	6	172	183	48	403
	7	173	297	132	602
	8	121	199	178	498
	9	16	30	47	93
II	10	110	227	134	471
	11	69	133	192	394
	12	131	184	144	459
	13	1	2	24	26
	14	124	262	200	586
	15	13	17	12	42
	16	16	99	53	168
	17	0	2	24	26
	18	0	10	75	85
	19	13	0	7	20
Subtotal		477	936	888	2301
III	20	11	10	102	123
	21	17	53	46	116
	22	2	1	35	38
	23	11	23	57	91
	24	0	0	22	22
Subtotal		41	87	262	390
TOTAL		1951	3061	1989	7001

Results and discussion

In the first analysis, the heuristic subprocesses (Pitt 1983) used by the three groups were compared using a repeated measures ANOVA. The processes represent a general approach to solving problems. The faculty were superior (F112 = 6.375, p = .013) in Interpreting Data, the third subprocess (see Table 2). They provided more responses that represented matching data to predictions (SR20), deriving patterns from the data (SR22), and drawing conclusions (SR24). No statistically significant differences were detected among undergraduates, graduates, and faculty on the first two subprocesses, Definition of Problem ($F_{2,69}$=.490, p = .614) and Data Acquisition (F2,24 = 1.20, p= .318). The less experienced groups used more responses to identify assumptions (SR2) and formulate hypotheses (SR7), as well as to organise the data (SR19). Although the number of responses differed considerably across groups in the first two subprocesses, the variability was so large that no statistically significant differences were detected. The cognitive process limitations of the student groups were revealed when they were asked to interpret the data. The undergraduates often relied on personal experience, while the graduates possessed the knowledge structure but could not apply it readily in a practical setting.

As noted previously, the subroutines were also grouped into six problem-solving strategies. The ranking of strategies according to number of responses was similar between undergraduates and graduates (Ennis and Safrit, in press). The faculty responses, however, yielded a different ranking from either of the two student groups. The correlation between the undergraduate and graduate rankings was .98. Much lower correlations, .41 and .37, were obtained for the undergraduates and graduates respectively, when compared with the faculty rankings. The highest ranking of the undergraduate and graduate groups represented the Evaluation strategy, while the faculty utilised the Basic Heuristics most often. The latter strategy can best be described as a forward approach to solving problems that are not extremely complex, suggesting that the faculty did not consider the simulated problems to be difficult.

Group comparisons by strategies

Group comparisons by strategies were analysed using a chi square test. The faculty gave fewer responses representing the Evaluation strategy ($\chi^2_{2.4}$ =32.62, *p* = 0.0001). Student groups more frequently referred to listing assumptions (SR2), selecting evaluative criteria (SR4), assigning priorities (SR5), and listing relevant information (SR6)—all low level subprocesses. They were also more likely to edit algorithms (SR 15) than the faculty. Conversely, the *Hypothetico-Deductive* strategy was employed more often by both graduates and faculty than by undergraduates ($\chi^2_{2.3}$ =177.10, *p* = 0.0001). The graduates more frequently formulated hypotheses (SR7), although both graduates and faculty were more likely to define predictions associated with hypotheses (SR8) and determine the truth value of a prediction (SR21). Faculty were superior in matching data to predictions (SR20). It appeared that the undergraduates were unable systematically to generate and test hypotheses.

Graduate students and faculty also used the means-ends strategies in the *General Problem Solver* more frequently than undergraduates. The faculty were more likely to define the goal state (SR11) although the graduates clearly defined the initial state (SR10) and identified the data needed (SR12). The faculty were superior to both undergraduates and graduates in using the *Feedback* strategy ($\chi^2_{2.4}$ = 80.86, *p*=0.0001). They identified feedback (SRI 7) throughout the simulation and tagged new information (SR18), but were not superior in organising data (SR19). Feedback identification was easier for the faculty, who were then able to use it to refine the solution chain.

It should be noted that subroutines within the General Problem Solver and the Feedback strategies were used by graduate students and faculty when the problem was not considered difficult. With both groups, the verbal protocols suggested that the subjects were *teaching* the examiner by providing a detailed rationale or comparison of the problem state and the goal/solution state. This explanation was often accompanied by an extensive review of the solution chain. Interestingly, when both the graduate and faculty groups attempted to explain the process, they slipped from the hypothesis testing (forward chaining) process to the less cognitively sophisticated means-ends or backward chaining procedure. This raised the possibility that these groups may structure lectures to teach problem-solving to undergraduates based on the inferior comparison strategies of means-ends analysis. If this is the case, undergraduates would be better prepared to solve clearly stated (goal-oriented) problems such as those found in textbooks or laboratory manuals. Conversely, more ambiguous, open-ended problems consistent with those found in clinical settings would be more difficult for undergraduates to solve within the limited General Problem Solver strategy. It is possible, however, that novice learners assimilate material more effectively in the goal-oriented format particularly as the complexity of the topic *increases* and the nature of the problem becomes more multifaceted.

The *Basic Heuristic* ($\chi^2_{2.6}$ = 246.3 *7*, *p*= 0.0001) and the *Pattern Extraction* ($\chi^2_{2.1}$ = 18.12, *p*= 0.0001) strategies were predominantly applied by faculty. They were more likely to list given information (SR 1), along with a set of available algorithms (SR 13) to facilitate the problem solving process. Only the faculty group provided output conclusions (SR24). Within the Pattern Extraction strategy, faculty tended to be better at extracting patterns from the data (SR22) and summarising relevant patterns (SR23) that led directly to a problem solution. The faculty's use of the advanced level strategies suggested additional knowledge and experience that placed them within the 'expert' category. Although expertise often demands extended periods of study, it is clear that extensive practice is not in itself a sufficient condition for becoming expert (Chi *et al* 1981). The strategies used to process and store knowledge for future retrieval are critical to an individual's ability to use forward problem-solving. In this study, faculty and graduate students were more adept at retrieving and reorganising knowledge when challenged by a 'difficult problem'. In studies of computer programming expertise, Rist (1989) found that experts simply retrieved the appropriate plan from memory and placed it correctly within the developing problem schema.

Conversely, undergraduates appeared unable to retrieve the basic declarative of formal knowledge and the accompanying algorithmic representations necessary to solve the problem using a hypothesis testing strategy. Instead, they attempted to create schema to match the problem goal when the required hypothesis testing plan was not already stored in memory. Although the undergraduates had completed prerequisite courses that included the necessary physiological information, they were unable to retrieve the required knowledge or to organise it within a hypothesis testing strategy. Thus undergraduates reverted to means-end strategies, frequently relying on knowledge of their own past performances on physiological tests and their personal responses to exercise programs. The inability to retrieve fundamental knowledge necessary for problem-solving limited the undergraduates' ability to visualise the problem solution. Rist (1989, 392) argued that 'the ability to represent parts of a solution underlies the ability to design a complete solution using those parts, so the lack of knowledge of the novices precludes the use of abstract design'.

The use of personal knowledge as the referent for problem solution is consistent with the use of incomplete self-explanations by students in the Chi et al (1981) study. In this study students often failed to generalise from examples, primarily because they did not understand the principles exemplified in them. Within the verbal protocols in this study, students generated their own examples that often (a) did not apply to the exercise principles being examined or (b) did not incorporate the knowledge base available to the faculty members. In most instances when novices searched their own experiences for a problem solution, the combination of the means-end solution design and incomplete or inaccurate data resulted in a more circuitous route to solution.

Graduates and faculty at times also abruptly changed both the level of detail of their solution strategies and the direction of problem design. When working with a familiar problem, graduates and faculty used the hypothesis testing approach detailed within a forward problem solving design. The protocol analysis revealed that in these instances, the solutions were articulated fluidly and with a minimum of irrelevant or extraneous information. However, when asked to apply the principles in a new or less familiar problem, the solution strategies reflected a greater number of the characteristics of the novices. Solution chains exhibited a move to analyse the goal followed by a backward design that synthesised knowledge in a less efficient and less complete strategy. Only in these problems where subjects were challenged within their level of expertise did they use the hypothesis testing of forward-chaining strategies. In these instances, subjects were able to retrieve the necessary knowledge and organise it using patterns probably developed during previous successful problem solving attempts. The results of this research suggested that subjects' use of hypothesis-testing strategies was consistent with both their knowledge retrieval and level of familiarity with the problem set. The results also provided evidence of the validity of the computer simulation by demonstrating that novices, more advanced subjects, and experts sometimes used different strategies to solve problems in the simulation. Further research is needed to examine the progressive sequencing of problems in order to facilitate retrieval of useful knowledge and effective solution strategies.

Findings of this research suggested that teachers should be alert to the importance of relevant problems and the difficulty of applying formal or declarative knowledge when attempting to increase the problem-solving ability of novices. Because novice learners frequently use personal experiences as primary sources of prior knowledge, it is imperative that educators anticipate this behaviour and assist learners to apply their prior knowledge appropriately in the solution of novel problems. Of greater difficulty appears to be the problem of convincing novice learners that in some situations personal experience is *inadequate* to generate rules and algorithms necessary for problem solution. In these instances trial and error or backward chaining strategies may be a necessary first step when motivating learners to acknowledge the usefulness of the declarative knowledge base in the problem solution.

Teachers should also be aware of the difficulties that *novice* learners experience in applying declarative knowledge to the problem solution process. In this research. learners who acknowledged the relevance of the rules and algorithms still exhibited difficulty in using the information in an appropriate and timely manner. Instructors may need to progress even more deliberately in a step-by-step approach to demonstrate the relationship of the formal knowledge to problems arising in a clinical setting. Without this assistance novice learners are likely to resort to the exclusive use of personal experience to the detriment of clients and programme.

Instructors of more advanced learners should also be alert to deficits in problem-solving that limit ability to solve complex problems requiring higher levels of expertise. Advanced students should be encouraged to match current data to predictions and to search the data for relevant patterns that often lead to efficient problem solution. In addition they should be required to summarise the evolving patterns explicitly and articulate several possible solutions for consideration. There appears to be a tendency for the advanced learner to state the perceived correct solution without testing it adequately or generalising the findings to the development of basic rules and principles useful in the solution of similar future problems.

In summary the HAFA computer simulation appeared to be an effective tool for eliciting problem-solving behaviours from subjects involved in the clinical application of physiological information. The use of the Pitt (1983) problem-solving model effectively discriminated between the different ability groups based on the strategies and heuristics that they employed in problem solution. Learners at each level demonstrated different abilities to define and solve the problem based on their level of experience and ability to apply declarative knowledge to problem solution. Instructors alert to the progressive development of ability in problem-solving may facilitate this process encouraging the advancement of expertise.

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