THE TRAINING OF EXPERTS FOR HIGH-TECH WORK ENVIRONMENTS

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ABSTRACT

When a training program fails to markedly influence the development of high-tech complex skills (such as electronic troubleshooting), the failure can generally be traced to two sources. First, failure occurs when training is not based on clear and explicit models of the desired expertise. For problem solving expertise, specifications of the expert's internal strategic processes for handling complex problems and the particular forms of knowledge and skill that support the strategies are especially critical. Secondly, failure occurs because the training of complex mental skills often fails to consider the conditions that are needed for the development of cognitive expertise, though similar conditions for the development of advanced physical skills are well known. They include extensive, constructive practice sessions where "the game is played" (i.e., authentic problems are solved) under realistic conditions. For such practice to be constructive, the trainee needs commentary and guidance from a coach who, among other things, can model the desired (problem solving) performance and carefully sequence problems according to the trainee's progress, while at the same time providing external support in the form of problem solving hints and instructional information. This set of conditions requires the learner to adopt an active role in skill development and situates learning and extended practice in the context of real world problems. This instructional approach is in contrast to traditional, more passive skill training where the instruction amounts to telling students <u>about</u> a domain such as electronics rather than providing learning experiences for <u>doing</u> electronic problem solving.

A large research and development program is underway in the Air Force to train technicians for complex work environments in a manner that seeks to avoid these pitfalls. The Air Force Basic Job Skills (BJS) Research Program is examining the performance of technical experts in dozens of occupations to establish models of expertise as targets for training. Advances in knowledge engineering procedures such as those used in developing expert systems are being applied to specify in great detail the technical expert's strategies and supporting skill and knowledge bases. Of particular interest are dimensions of expert performance that cut across Air Force jobs and can thus be characterized as <u>basic</u> to expertise in complex work environments. In some sense these common dimensions can be viewed as modern day basic skills or the skills needed for a technologically advanced world. In addition, applications of artificial intelligence to instruction in the form of intelligent tutoring systems are being utilized to create the desired conditions for active, problem-oriented learning. In this paper, work done with over 15 experts in four related electronic and computer maintenance jobs will be highlighted to illustrate the "engineering" of expert knowledge. Also, a successful training study conducted with apprentice electronic technicians will be reported. In this study, the standard obstacles in complex skill training were satisfactorily overcome.

KNOWLEDGE ENGINEERING FOR INSTRUCTIONAL APPLICATIONS

Intelligent tutoring systems (ITS) offer the kinds of learning conditions that are thought to be important in the development of complex cognitive skills, i.e., guided practice in realistic problem solving. They require at least three types of knowledge bases as their infrastructure. First, there is the knowledge that constitutes expertise in the domain being taught. This is the expert model, which represents the goal state for trainees or the set of ideal performances the instruction should produce. Secondly, dynamic information about what a trainee knows and doesn't know is necessary to model student performance during learning. Since student performance data is needed so that instructional decisions can be made, some investigators have suggested that this knowledge base is best conceived as a layer of the third ITS information structure, the curriculum. Curriculum knowledge of course provides the subject matter content and instructional treatments that are intended to move students toward the goal of expertise as represented by the expert model. Accordingly, information about a student's performance and understanding may best be expressed in terms of *his/her status with respect to curriculum goals* and subgoals, e.g., proficiency in schematic tracing. A knowledge engineering methodology designed to generate these elements for the training of complex technical problem solving (e.g., electronic troubleshooting) has been developed as part of the Air Force Basic Job Skills Research Program. The methodology and illustrative results are described below.

<u>*Cognitive Task Analysis Methodology*</u>

The approach to knowledge engineering in the BJS effort involves real-time problem solving, multiple stages and types of knowledge engineering inquiry, and a number of formats for knowledge representation, some of which have been adapted from knowledge engineering work in medical diagnosis.

In the first stage of the process, hands-on technical experts in a particular AF specialty generate a set of authentic problem scenarios that are representative of all types of problems, i.e., faults encountered on their equipment systems. In the second stage, pairs of experts pose the scenarios to each other so that their work performance can be realistically sampled. (The expert who poses the problem knows the location of the fault; the expert who attempts to solve the problem does not.) During the solution process, the researcher probes the expert solver to establish the series of actions s/he executes in solving the problem. Reasons for the actions, interpretations of outcomes resulting from the actions, and block diagram-like sketches of the equipment affected by the actions and outcomes are recorded as well. This part of the knowledge engineering process corresponds to the generation of sequences of mental events called PARI structures (Precursor [to Action]-Action-Result-Interpretation). Comparable frameworks have been used in the engineering of medical diagnostic knowledge. (1) An example of PARI data is shown in Table 1 for a single action node.

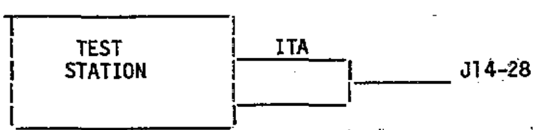
TABLE 1: PARI DATA

Precursor: Want to see if the stimulus signal is good up to test package cable.

Action: Measure signal at J14-28 with multimeter

Result: 28 volts

Interpretation: This is expected reading; this tells me that the stimulus is getting from the test station through the cable, so that part of the stimulus path is good



In the third stage, a series of rehashes occurs during which the researcher probes the expert for various kinds of information to elaborate and extend the PARI data, including the following: alternative results that could be expected as outcomes for a given action and interpretations of such alternative results; alternative actions to satisfy the same goal (as stated in the precursors); alternative precursor-action pairs that would be reasonable to pursue; reasons to support the selection and sequence of goals (precursors); reasons to support the expert's preferred actions; and finally, the specific knowledge and skills required to carry out each PARI sequence. Examples are shown in Table 2.

TABLE 2: Rehashes of PARI Data

(1) The technician is asked what other result(s) *would be expected as an outcome to each* action, and what that result would reveal.

Alternative Result 1: 0 volts

Alternative Interpretation 1: the problem is upstream from this measurement point; since the output is 0, the problem could likely be in a connection, or in the stimulus generator.

Alternative Result 2: 18 volts

Alternative Interpretation 2: the problem is upstream from the measurement point; since the output is low rather than 0, the problem is more likely to be in some component rather than in a connection.

(2) The technician is asked to generate alternative actions to satisfy the same goal (as stated in the precursor):

Precursor: Verify stimulus signal is good up to test package cable.

Alternative Action: Measure stimulus signal output from test station entering test package cable and then swap cable.

(3) The technician is asked to generate alternative precursor (goal) - action pairs that would be reasonable to pursue, e.g.,

Alternative Precursor: Want to see if measurement signal path is good.

Alternative Action: Insert a signal from a known good generator to the beginning of the measurement path.

In the final stage of the process, the focus of analysis shifts from PARI sequences for a single problem to the full complement of troubleshooting problems for a given job. The goals are to consider all instances of actions, goals (precursors), system diagrams, and supporting reasons and then classify redundant and related instances into appropriate categories. Tables 3 and 4 illustrate this process for actions and precursors. Once a skill category, such as "measurement taking," emerges, it becomes the basis for the final representation of a troubleshooting knowledge component, namely, a skill definition. The collection of skill definitions for a job domain serves the more detailed function of describing exactly how procedures are executed for purposes of instruction and assessment.

Making procedural skills clear enough for teaching and testing purposes requires an analysis of the subcomponents of the skill and the conditions under which the skill is activated. For example, measurement taking involves knowing the signal's expected value and type, selecting and operating the measurement device, and reading and interpreting the measured property. These subcomponents are apparent in

Table 1 PARI data. Procedural subcomponents and conditions provide a framework for generating progressively harder instances of the skill. For example, easy to hard instances of conditions calling for the selection of a measurement device would be elicited from the expert and then utilized as curriculum knowledge. The predetermined sequence would provide input to instructional planning.

Similarly, the three knowledge bases required for intelligent tutoring systems are provided: expert problem solving performance data represents the domain expertise; the problem set plus elaborations and skill definitions constitute the instructional content; and problem solving performance data for less-than-expert technicians both informs student modeling and highlights expert-novice differences in ways that suggest instructional tactics.

TABLE 3: Grouping/Classification of Action Instances (Procedures/Operations Component)

Action Instance	Procedural Category
-check pins on test package -check fault indicator light	• visual inspections
-swap Threat Simulator A5 card (probable cause of failure) -swap card N4A1 with like N4A3 card	• swapping
-run diagnostics on high frequency measurement card and coax switch -run diagnostics with bit dump	• computer control/software interpretation
-test for good signal out of TG4 with oscilloscope -ohm check between J110 and J4 with *digital multimeter* (DMM) -put N4A1 on extender and test for -18VDC with DMM	• measurement taking

TABLE 4: Grouping/Classification of Precursor Instances (Strategic Knowledge Component)

Precursor Instance	Goal Structure Category
- want to verify 5V power supply fail not a fluke - want to verify failed diagnostic not a fluke	• verify fail
- need more information on drawer serviceability - need more information on resources used in failed test - want to trace stimulus input to get complete routing	• expand information on probable cause of failure and its inputs/outputs
- want to test most likely suspect on stimulus path - want to check other cards in signal flow - want to check for good input signal at N4A1 (probable cause of failure) - want to check wiring between source of signal (N3A16 card) and N4A1 (probable cause of fail)	• test input/output suspects to probable cause of failure

Fine-grained problem solving information such as that described above is ultimately aggregated, summarized, and abstracted across problems and across experts' (and novices') solutions to provide a coherent statement about technical performance for a given job. Such characterizations constitute the aforementioned explicit models of expertise that determine the effectiveness of complex skills training.

Knowledge Engineering Results

Approximately 15 experts and 200 less-skilled technicians in four related AF electronics specialties have participated in knowledge engineering studies as described above as part of the Basic Job Skills Research Program. On the basis of these studies, a meaningful superstructure for organizing troubleshooting performance data has been developed: It consists of three major components: (1) system knowledge or the equipment device models used in problem solving (e.g., system knowledge regarding stimulus or measurement functionalities); (2) troubleshooting procedures or operations performed on the system; and (3) strategic knowledge, which includes (a) strategic decision factors that involve fault probabilities and efficiency estimates and (b) a top-level plan or strategy component that is responsible for component orchestration in task execution. The orchestration occurs as the Strategy component which sits on top of the Procedures and System Knowledge components deploys pieces of knowledge and procedural subroutines as needed and as driven by the decision factors (Figure 1).

System Knowledge. In this cognitive skills architecture (Figure 1), system knowledge provides the dominant organizing principle. For example, the System Knowledge component provides the foundation to which the companion Procedures component is attached. According to this view, a measurement or swapping operation is attached to a device model representation, since the purpose of the operation is viewed as adjusting the present model of the device with new knowledge of faulty components. Similarly, an information gathering procedure such as software interpretation is directed toward elaborating the available device model with instantiations and details relevant to the particular problem. System knowledge also feeds the strategic decision factors that underlie the strategy component, since these factors involve system fault probabilities and efficiency estimates associated with operations on the system. Finally, system knowledge influences the goal structure of the general strategy component in the sense that certain areas of the equipment are targeted before others (again due to fault probabilities and efficiency considerations).

Procedures/Operations. During problem solving, expert electronics technicians adjust their model of system operation by performing two major classes of actions. The first class involves troubleshooting operations performed on the system, and the second consists of information gathering procedures that use external sources of system information. Action statements in PARI sequences provide the raw data source for this component.

Troubleshooting operations such as running a test or making a measurement typically refine the expert's belief about the location of the fault. In effect, the operations mark some portions of the equipment system as more suspect than

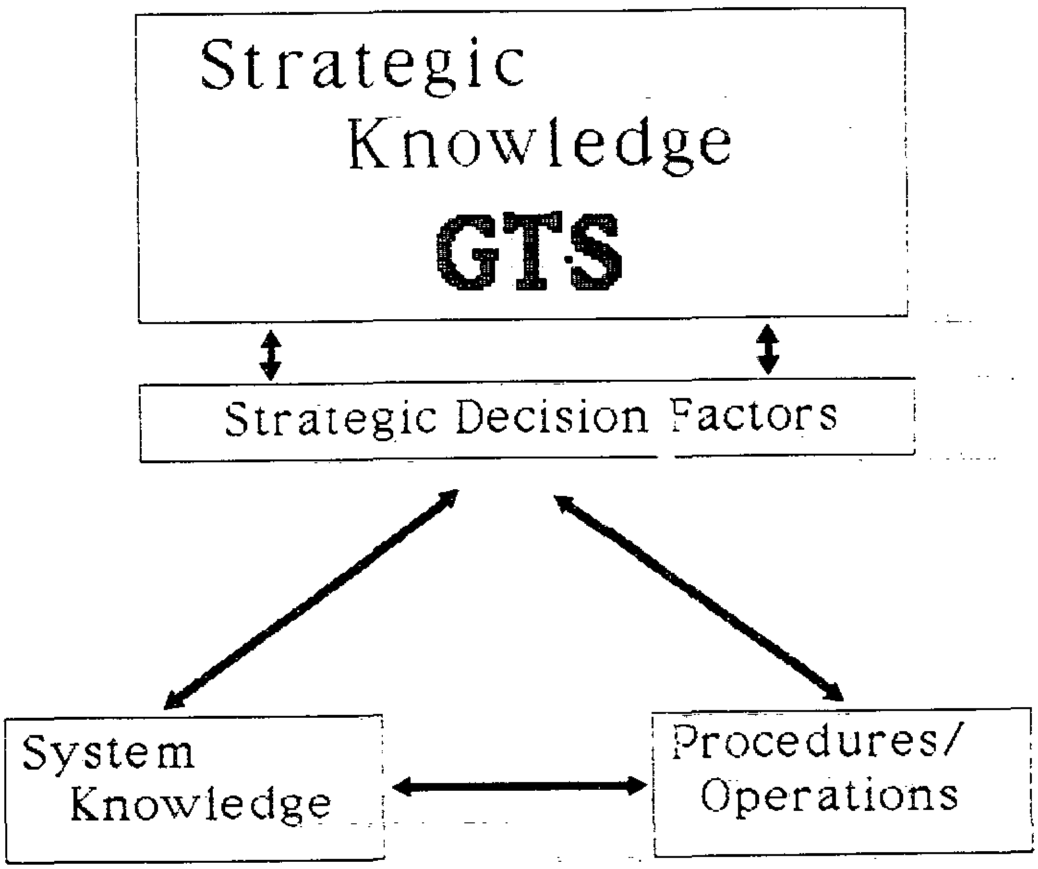


FIGURE 1: Cognitive Skills Architecture

others. The expert can then focus attention on the suspect components and elaborate a localized device model by either remembering more precisely how the suspect sections work or by learning about its operation by consulting external information sources. These sources include technical data or documentation sources such as schematic, wiring, and block diagrams; computer software; and the actual physical equipment itself.

Strategic Knowledge. Finally, there is the strategic component of the architecture shown in Figure 1, with its underlying strategic decision factors. When knowledge engineering is conducted for developing an intelligent tutoring system, it is particularly important to make explicit the factors that experts consider in deciding (a) how to sequence their fault isolation goals and (b) which troubleshooting operation or procedure to use in pursuing a specific subgoal. Data from the BJS project plus related research in troubleshooting suggest that these factors are based on three fundamental principles--probability, cost, and benefit.

Probability refers to the likelihood that a certain system component is defective. One kind of probability factor is the base rate of failure for a component. One section of the equipment may be more suspect than other equipment sections simply because one component generally breaks more often than the others. A second probability factor involves the association between system components and particular symptoms. For example, a zero volts fail makes connections more suspect than if a low voltage reading had been obtained. The latter would have implicated devices rather than connections.

Cost decision factors, or the obstacles in performing troubleshooting operations, can be represented as follows:

- Time: the longer an operation takes, the less preferred it is by the expert.

- Danger: the more dangerous an operation is (either to an operator or to the equipment), the less preferred it is.

- Dollars: the more expensive an operation is, the less preferred; e.g., repairing a component is favored over replacing it.

- Mental energy: the more mentally demanding an operation is, the less preferred.

- Physical energy: the more physically demanding, the less preferred.

Benefit decision factors primarily involve the quantity and quality of the information gain. Tests that generate more information about the signal path, for example, are favored over less informative tests. Experts prefer measurement over swapping for this reason, among others. Tests that are more reliable are favored as well, and so swapping may be preferred over a diagnostic self test having known unreliability.

To summarize, a primary source of failure in complex skills training programs, namely, deficient models of the targeted expertise, has been attacked analytically in the Air Force BJS research effort. A methodology that blends techniques from knowledge engineering and cognitive task analysis has made explicit the unobservable mental processes of expert troubleshooting and produced specific expert models to use as targets of instruction. Results have shown that the prototypical troubleshooting performances of AF technical experts in four related high-tech specialties are a function of three major classes of mental events - strategic knowledge, system understanding, and procedural skills interact in elaborate ways as the complex decision making involved in fault isolation unfolds. These characterizations of expertise are in turn treated as the expert models for intelligent tutoring systems which provide interactive learning environments capable of overcoming the other major obstacle to complex skills training. The curriculum and student knowledge bases required by intelligent tutoring systems can also emerge from knowledge engineering output of this type. A training study involving instruction which was developed in this way is described next.

A SUCCESSFUL TRAINING STUDY

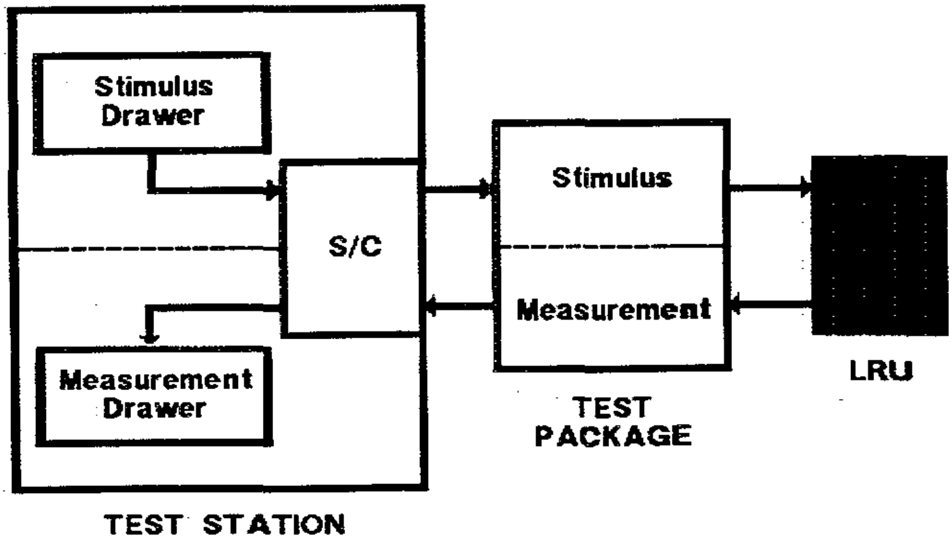
As a precursor to a BJS intelligent tutoring system to teach troubleshooting, a training study involving a human tutor (versus a computer coach) was conducted. The domain was F15 integrated avionics maintenance at the intermediate level of repair (automatic test equipment). The three ITS knowledge bases described above were established via cognitive task analysis and utilized in the instruction.

System (device model) knowledge, troubleshooting procedures/operations, and strategic knowledge were engineered for a group of expert, novice, and intermediate level avionics technicians on a constrained set of fault isolation problems. The expert-like skills targeted for enhancement were particular instantiations of the Figure 1 cognitive skills architecture. The system knowledge of interest was an abstracted characterization of the avionics system signal path, plus several layers of elaborated system knowledge. As shown in Figure 2, the path reveals the stimulus and measurement functionalities of the equipment system. The signal originates in the stimulus drawer of an avionics test station, travels through the station's switching drawer (S/C) which performs signal switching functions, and through an interface test package to an aircraft line replaceable unit (LRU) which is being tested for a malfunction. It returns through the interfact package to a measurement source in the test station. The procedures of interest were three methods for investigating the equipment that ranged from rudimentary to advanced:

(1) swapping equipment components
(2) using self-diagnostics to test system integrity
(3) measuring device and circuit functionality

Increasingly complex system and strategic knowledge are associated with increasingly sophisticated methods. For example, the swapping model draws upon superficial system knowledge where suspect components need only be known in the nominal sense, whereas detailed and functional device models are needed to support the measurement model. The self-diagnostics model requires knowledge of the relative reliabilities and information gains associated with the available self-diagnostic tests, whereas

FIGURE 2: **Avionics Equipment Configuration (Signal Path)**



reasoning about the costs and benefits associated with swapping procedures tends to be relatively simple. In addition to detailed system knowledge, the measurement model also requires complex decision making regarding where and how to take measurements as well as supporting skills to identify test points (schematic tracing) and to interpret measurement outcomes accurately.

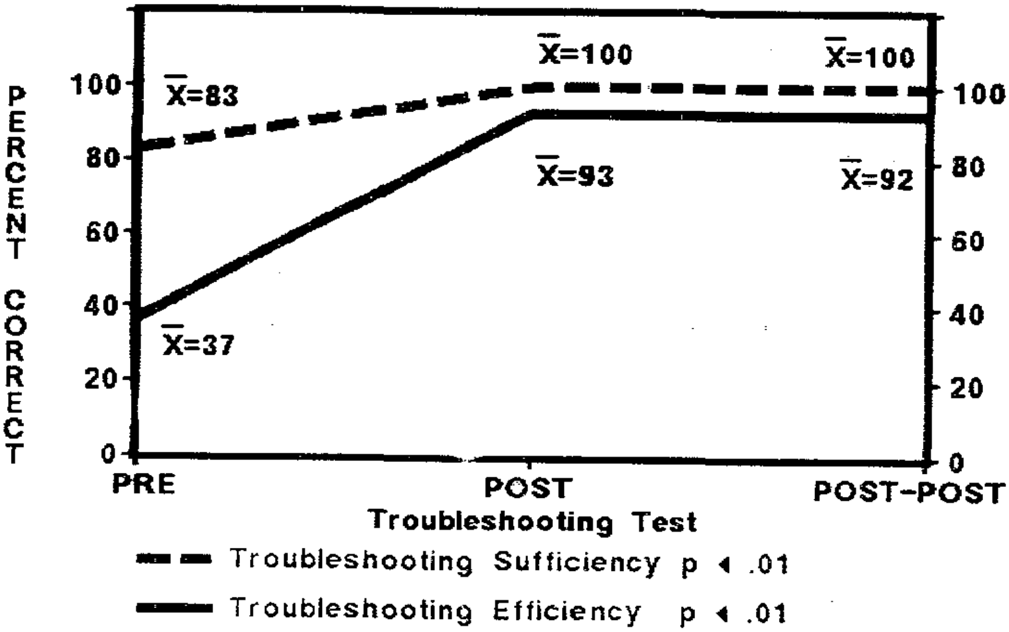
The treatment in the training study involved the posing of authentic troubleshooting problems similar to those generated in a BJS knowledge engineering study as described above. During three to five hours of individual instruction over a period of three days, seven technicians were tutored. They were presented a troubleshooting scenario and then probed regarding what they would do to isolate the fault (Actions), why they would take the particular action (Precursors), and what the outcome (Result) of the action meant to them (Interpretation). In effect, technicians were instructed to generate PARI records (see Table 1) including the associated device model sketches. The human tutor gave feedback to their stated Precursors, Actions, and Interpretations in the form of hints intended to move them toward more expert-like performances.

To evaluate their learning, they were given both an end-of-training problem-based test as well as a delayed posttest after the weekend. The tests were authentic troubleshooting scenarios belonging to the same class and difficulty of problems on which they had been tutored. Their progress was scored both in terms of the sufficiency of their operations--that is, whether they sufficiently investigated all suspect pieces of the equipment--and the efficiency of their moves--that is, whether they efficiently conserved time and equipment resources.

Results showed statistically significant improvements in both areas, with particularly dramatic gains in efficiency. Mean scores are *plotted in Figure 3. The group's Sufficiency in* examining all suspect parts of the equipment improved from a pretest mean value of 84 (range = 60 to 95) to a posttest mean of 100. The delayed posttest mean was also 100, indicating the improvement was retained over the weekend. The group's Efficiency in fault isolation improved over twofold. The mean pretest value was 37 (range = 24 to 52); the initial posttest mean was 92 (range = 81 to 100); and the delayed posttest mean was 93 (range = 81 to 97).

Pedagogically, this human tutor training study was based on the same instructional input and principles that underpin the avionics intelligent tutoring system. Expert models of performance provided the ideals used as instructional goals. Less-than-expert performance data provided the basis for a curriculum progression. MOre specifically, students were tutored along a progression of fault isolation methods that ranged from swapping to diagnostic testing to measuring. The progression was based on execution difficulty as demonstrated by the range of technicians studied in the task analysis phase of the work. Finally, the instruction took place in an active, problem-oriented learning environment designed to foster comples skill acquisition. Technicians were afforded extensive proctice in fault isolation; they were required to articulate and focus on their reasons and their interpretations of various troubleshooting moves; they were aided by a human tutor who principally through Socratic dialogue, challenged them to reflect on what they did in terms of expert standards of throughness and efficiency. The technicians later attributed the gains they made to the opportunities they had to practice fault isolation procedures intensively and solve problems independently. They reported that recording and reflecting on their actions and reasons was helpful and that they profitted from the hints and consistent feedback.

FIGURE 3: **BJS Proof of Concept Training Study**



This successful study is viewed as empirical support for the effectiveness of skill acquisition treatments that are driven by explicit expert models and characterized by learning conditions vital to the development of cognitive expertise. A more substantial proof of concept will occur during late 1987 when a BJS avionics intelligent tutoring system providing 50 hours of instruction will be operationally tested in three AF workcenters (2,3).

ABOUT THE AUTHOR

Dr Gott is a senior research scientist and Project Director of the Air Force Basic Job Skills Research Program at the Air Force Human Resources Laboratory. She holds an MA and PhD in Educational Psychology and has ten years experience in psychological research and development. Her current research interests are in the investigation of complex problem solving skills in advanced technical domains. More specifically, her work since joining AFHRL in 1979 has centered around the application of new analytic and instructional approaches coming out of basic research in the cognitive sciences (including artificial intelligence research) to the skill assessment and training problems facing the Air Force.

Dr Pokorny is a research scientist on the AF Basic Job Skills Program. He holds a PhD in Experimental/Cognitive Psychology and is currently interested in knowledge engineering techniques for use in developing complex skills tutoring systems.